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Growing like China: Firm performance and global production line position☆

Davin Chor[a], Kalina Manova[b,*], Zhihong Yu[c]

[a] Dartmouth and NBER, USA
[b] University College London and CEPR, UK
[c] University of Nottingham and CESifo, UK

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ABSTRACT

Global value chains have fundamentally transformed international trade and development in recent decades. We use matched firm-level customs and manufacturing survey data, together with Input-Output tables for China, to examine how Chinese firms position themselves in global production lines and how this evolves with productivity and performance over the firm lifecycle. We document a sharp rise in the upstreamness of imports, stable positioning of exports, and rapid expansion in production stages conducted in China over the 1992–2014 period, both in the aggregate and within firms over time. Firms span more stages as they grow more productive, bigger and more experienced. This is accompanied by a rise in input purchases, value added in production, fixed costs incurred, and profits. We rationalize these patterns with a stylized model of the firm lifecycle with complementarity between the scale of production and the scope of stages performed.

1. Introduction

Global value chains (GVCs) have fundamentally transformed international trade and development in recent decades (Baldwin, 2016; Antràs, 2021; World Development Report, 2020). For individual firms, new challenges and opportunities have arisen as production has fragmented across firm boundaries and country borders. For aggregate economies, new policy questions have taken center stage: How do GVCs affect firm performance in the short run and growth prospects in the long term? If global production

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* Corresponding author.
E-mail address: k.manova@ucl.ac.uk. (K. Manova).

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lines enable firms in advanced economies to profitably offshore, do they also engender cross-border technology transfer and structural transformation in less developed countries, or do they instead entrench such countries in low-profitability, low-growth GVC activities? Despite great policy interest, only recently has academic research begun to overcome data and conceptual challenges to dispel common speculation and uncertainty around these issues.

In this paper, we take first steps towards documenting how firms position themselves in GVCs and how this position evolves with productivity and performance over the firm lifecycle, using matched firm-level customs and manufacturing survey data for China. China provides a fascinating context in which to study the implications of global production sharing for firm and aggregate growth. As the fastest growing economy over the last 30 years, China recently became the second largest country by GDP and the biggest exporter in the world. Key to this economic transformation has been its dramatic globalization, marked by its joining the WTO in 2001 (Feenstra and Wei, 2010).[1] Indeed, various trade and industrial policies have encouraged firms' participation in GVCs, such as the formalization of a processing trade regime under which foreign inputs can be imported duty-free for further processing, assembly and re-exporting (Manova and Yu, 2016), or the establishment of special economic zones that concentrate trade and FDI activity.

Our first contribution is to characterize Chinese firms' position in GVCs and trace its evolution over the 1992–2014 period. We exploit detailed Input-Output Tables for China to build an industry-level measure of *upstreamness* for 135 industries. Introduced by Fally (2012) and Antràs et al. (2012), this measure captures an industry's distance to final demand in terms of the weighted average number of stages at which the industry is used as a production input before it reaches final uses (i.e., consumption or investment). Higher values are associated with more upstream sectors (e.g., rubber), and lower values indicate sectors that are more proximate to final demand (e.g., cars).

We quantify Chinese firms' global production line position by combining this industry measure of upstreamness with detailed information on the product composition of firms' trade flows. This allows us to construct weighted-average upstreamness measures of a firm's imports, U^M, and of its exports, U^X. The difference between the two, $U^M - U^X$, is thus informative of the span of production stages that the firm undertakes within China, either by directly performing these or by outsourcing to other suppliers in China. The Chinese customs data permit us to construct these measures at the firm level for 2000–2014. We are further able to draw on province- or city-level customs data for earlier years, to analyze trends in the upstreamness of China's aggregate trade flows for the more extended period of 1992–2014.

We identify three *Macro Trends* in China's GVC participation. First, over 1992–2014, Chinese imports became significantly more upstream, while Chinese exports became slightly more proximate to final demand. Of note, these trends tapered off after 2008, coinciding with when China's trade-to-GDP ratio reached its peak and started to moderate (IMF, 2016; Frankel, 2016). These developments were mainly driven by ordinary trade, rather than by flows administered under processing and other trade regimes. Second, using a formal decomposition, we show that the rise in aggregate import upstreamness between 2000 and 2014 is explained by both the net entry of firms that tend to import further upstream (the extensive margin) and by within-firm increases in import upstreamness (the intensive margin). Third, we exploit regressions with firm and year fixed effects to confirm that within firms over time, imports became significantly more upstream, exports became moderately more proximate to final demand, and the implied span of production stages performed in China increased quickly during 2000–2014.

Our second contribution is to establish new stylized facts about the relationship between Chinese firms' attributes, production line position, operations, and performance over the firm lifecycle. We document three *Firm Facts* about the evolution in activity within firms over time. First, when firms become more productive, bigger or more experienced, they import significantly more upstream, export moderately closer to final demand, and span more production stages in China. These results hold across different measures of firm productivity (real value added per worker, revenue-based TFP estimates à la Olley-Pakes, Levinsohn-Petrin, or Ackerberg-Caves-Frazer), firm size (sales, employment), and firm experience (age, cumulative past trade activity).

Second, when firms span more production stages (in China), they increase their value added in production, total purchases of material inputs, and use of labor inputs (as captured by the total wagebill), all proportionately with output. Third, when Chinese firms perform more production steps, they also raise their fixed costs and assets (proxied respectively by inventory holdings and by net plant, property and equipment), and earn higher profits. Of note, profit margins – in terms of profit-to-sales, profit-to-value-added, or profit-to-assets ratios – remain largely unchanged.

We establish these three *Firm Facts* with a baseline specification that controls not only for firm fixed effects, but also for sector-by-year fixed effects that absorb any common supply and demand shocks at the industry level. We have found these patterns to be robust under extensive sensitivity checks. The results hold whether or not we further condition on firm-level measures of skill intensity (average wage), capital intensity (net fixed assets per worker), or the share of processing trade. The *Firm Facts* pertaining to the span of production stages, $U^M - U^X$, hold also when we control directly for the upstreamness of the firm's exports, U^X, to capture where along global production chains the firm is positioned relative to final demand. We have also obtained similar patterns with alternative constructions of the firm-level upstreamness measures, such as when we drop imports and exports of non-manufacturing products, or of mineral products more specifically.

Our third contribution is to develop a partial-equilibrium model of a firm's decision over where to operate along the production chain and which production stages to perform in order to maximize its profits. Our goal is to provide a baseline conceptual framework that can rationalize the *Firm Facts* in the data and highlight key economic mechanisms at play, rather than to fully characterize firm interactions, price-setting and market-clearing in general equilibrium.

[1] Brandt et al. (2008) quantify the contribution of two other sources of structural transformation to China's phenomenal growth over 1978–2004: large-scale reallocations from agriculture towards manufacturing and services, and from state-owned enterprises towards private firms. At the same time, Hsieh and Klenow (2009) conclude that there is still extensive misallocation of productive resources across Chinese firms compared to the US.

In the model, price-taking firms purchase intermediate inputs from upstream suppliers, add value in processing these into more complete products along a sequential production line, and sell their output in competitive markets. Each firm faces decisions on how upstream (or unfinished) an intermediate input to purchase, and on how proximate to final demand (or finished) an output to produce; these in turn determine the firm's span of production stages. Looking upstream, firms face a trade-off between sourcing a more fully processed but more expensive input and incurring the fixed and variables costs of performing the inframarginal production steps. Looking downstream, firms likewise weigh the benefit of selling a more finished output at a higher market price against the fixed and variable costs of undertaking more production stages. We show that when these inframarginal fixed and variables costs are relatively small, the model implies a complementarity between the scale of a firm's production and the scope of stages it performs: an exogenous positive shock to productivity would induce the firm to both span more production stages and operate on a bigger scale, ultimately earning higher profits.

Through the lens of this stylized model, we interpret our first *Firm Fact* as consistent with a causal effect of changes in a firm's productivity on its optimal production line position. This interpretation extends to the findings for firm size and experience, to the extent that more productive firms have higher survival probability and changes in firm size arise from underlying shifts in firm productivity. In line with this causal interpretation, we report additional empirical results based on an instrumental variable approach: We adopt an IV for firm productivity or for firm size that captures how exposed Chinese firms are to plausibly exogenous shocks to foreign demand.[2] On the other hand, we view our second and third *Firm Facts* as correlations among joint outcomes of the firm's profit maximization problem that reflect optimal operational decisions and resulting profits.

Our findings shed light on policy questions about the implications of GVCs for firm growth, and challenge concerns about GVC-induced stagnation traps. The new evidence we uncover suggests that the fragmentation of production across countries can enable firms to first specialize in narrower segments of GVCs and gradually expand into more production stages, grow their production scale, add more value, and earn higher profits. While we do not explicitly incorporate this consideration in our model, this growth path may be especially important in emerging economies where less productive and less experienced firms stand to gain more from knowledge transfer from foreign buyers and suppliers. Credit constrained firms may likewise be able to start by operating fewer production stages, in order to accumulate retained earnings and use internal capital to fund subsequent expansion along the supply chain. The firm lifecycle facts we have uncovered in a world with GVCs therefore point to potential macro-level implications that future work can explore.[3]

Our work contributes to several strands of research. We extend a growing literature in international trade on the rise of GVCs. Early empirical analyses have aimed to infer the country origins of value added embedded in country-level trade flows, and documented the increased fragmentation of production across borders (e.g., Hummels et al., 2001; Yi, 2003; Johnson and Noguera, 2012; Koopman et al., 2014). Much subsequent work has emphasized the important role of international supply chain linkages for firm operations. Successful exporters routinely use a large share of imported inputs in producing for foreign markets (e.g., Bernard et al., 2012). This is especially true in developing economies, where the range, cost and quality of domestic intermediates may be ill-suited to manufacturing products that meet the quality standards of foreign consumers and the technological needs of foreign downstream producers (e.g., Kugler and Verhoogen, 2009, 2012; Bas and Strauss-Kahn, 2015). Indeed, more than half of Chinese exports are conducted under processing trade, and the large majority of Chinese exporters intensively use imported inputs (e.g., Manova and Zhang, 2012; Wang and Yu, 2012; Manova and Yu, 2017).

We specifically advance recent work on global production lines, in which the production process is viewed as a technologically sequenced series of stages. We provide one of the first firm-level analyses and document novel stylized facts that speak to the relatively small body of existing models in this literature. At the aggregate level, Costinot et al. (2013) examine how cross-country productivity differences affect the span of stages that countries specialize in. Fally (2012) and Antràs et al. (2012) conceptualize and empirically implement measures of the upstreamness of different industries along production chains. Antràs and de Gortari (2020) build and quantify a model that explores how the geography of trade costs affects the equilibrium formation of global production chains. In a related line of work, Antràs and Chor (2013) and Alfaro et al. (2019) investigate how firms that operate in sequential production chains would optimally organize their sourcing strategies, vis-à-vis whether to integrate within firm boundaries or outsource to arm's length suppliers the procurement of each customized stage input. While their predictions are often rich and subtle, these existing models do not fully rationalize the new patterns we uncover in the Chinese data.

To the best of our knowledge, we present a first analysis of the relationship between firms' inherent attributes, production line position, internal operations, and performance over the firm lifecycle. This provides a bridge between research by trade economists on GVC activity, and research by development, industrial organization, and macro economists on firm growth and structural transformation. Prior studies have linked access to imported inputs and learning from foreign partners to firm productivity growth (e.g., Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Goldberg et al., 2010; Halpern et al., 2015), examined trade-related growth in productivity and domestic value added within Chinese firms (e.g., Brandt et al., 2012, Kee and Tang, 2016, Tang et al., 2020), and showed that processing trade can be a stepping stone to higher value added, more profitable and more liquidity-intensive ordinary trade in the presence of financial frictions (e.g., Manova and Yu, 2016). A separate line of research has identified systematic patterns at both the country and firm levels in the expansion of product scope and in the transition across products,

[2] We have also implemented an alternative IV based on each Chinese firm's exposure on the import side to rest-of-the-world trade shocks. This builds off the idea that increased access to imported inputs can raise firm productivity. The results obtained are very similar; see Section 4.2.2.

[3] Recent work suggests that heterogeneous dynamics and shock propagation across firms can indeed have sizeable effects on macro-economic outcomes. For example, Di Giovanni et al. (2018), Kramarz et al., 2020, and Gaubert and Itskhoki (2018) find important effects of micro-level granularity on exposure to foreign demand shocks, international business cycle comovement, and comparative advantage in the aggregate.

based on similarity in input use, upstream-downstream production links, or progression towards greater technological sophistication (e.g., Hausmann and Klinger, 2007; Bernard et al., 2010; Boehm et al., 2019). A growing body of work has examined price-setting and rent-sharing along supply chains, using buyer-supplier data from markets in developing countries characterized by small upstream producers and large downstream processors and distributors (e.g., Macchiavello and Miquel-Florensa, 2017; Macchiavello and Morjaria, 2019; Cajal-Grossi et al., 2020).[4] Finally, there is a long tradition of studying the internal span of control in models of firm boundaries with (dis)economies of scope and scale (Coase, 1937; Williamson, 1981; Becker and Murphy, 1992; Kikuchi et al., 2018; Fally and Hillberry, 2018).

The paper is organized as follows. Section 2 introduces the data and the industry measure of upstreamness. Section 3 uncovers *Macro Trends* in China's position in GVCs during 1992–2014. Section 4 establishes *Firm Facts* about the joint evolution of firm attributes, production line position, production activities, and performance over the firm lifecycle. Section 5 presents a model of firm behavior that rationalizes the empirical patterns. Section 6 concludes. The online appendix contains all theoretical proofs and supplementary tables and figures.

2. Data

2.1. Trade statistics

We examine the evolution of China's international trade activity over 1992–2014 using three comprehensive datasets from the General Administration of the Chinese Customs. The first dataset covers the 1992–1996 period. It reports the value of total exports and imports in US dollars for each Chinese province, HS 6-digit product (about 5,000 categories), firm ownership type, and trade regime. The second dataset provides slightly more disaggregated data for the years 1997–1999. It records the value of total exports and imports in US dollars for each Chinese city, HS 8-digit product (about 6,500 categories), firm ownership type, and trade regime. We will use these first two datasets to shed light on aggregate trends in import and export upstreamness for China during the 1990s.

The third dataset – the Chinese Customs Trade Statistics (CCTS) – comprises the universe of China's international trade transactions in 2000–2014. We observe for this period the value of firm-level exports and imports in US dollars, by HS 8-digit product, firm ownership type, and transaction trade regime. To abstract from the seasonality and lumpiness inherent in monthly trade flows, we aggregate this raw data to the annual level. When appended to the first two datasets, this extends our coverage of country-level trends to the entire 1992–2014 period. At the same time, the CCTS provides our core sample for any firm-level regression analyses that we conduct.[5]

The Chinese customs records allow us to distinguish between several firm ownership structures and operational modes. For ownership, the data separates out trade flows that are conducted respectively by private domestic firms (PVT), state-owned enterprises (SOE), joint ventures (JV), and foreign-owned multinational affiliates (MNC). We also observe the volume of trade conducted under various institutionally sanctioned regimes. For 1992–2006, we observe a full breakdown into ordinary, processing, and a residual category of "other" trade regimes; for 2007–2014, however, the data include only a breakdown between ordinary and non-ordinary trade, with the processing and "other" trade regimes reported as a single category. The processing trade regime has played a prominent role in China's growth as a manufacturing hub, as it permits firms to bring inputs into China intended for further processing, assembly and re-exporting on behalf of a foreign buyer without incurring import duties. Firms are allowed to simultaneously conduct both processing and ordinary trade activities, and in practice about 25% of all exporters do so (Manova and Yu, 2016).

Our sample period covers the dramatic expansion in China's export and import activity. Over 1992–2014, China's exports rose from about \$84.9 billion in 1992 to close to \$2.34 trillion in 2014 (in current U.S. dollars), with a noticeable acceleration after China's accession to the WTO in 2001.[6] This aggregate expansion was accompanied by substantial variation in trade participation across firms. The number of firms engaged in exporting more than quadrupled from 62,746 in 2000 to 298,493 in 2014. Average exports per firm doubled from \$3.97 million in 2000 to \$7.85 million in 2014, with large standard deviations around these means (\$41.5 million in 2000 versus \$102.4 million in 2014). On the importing side, we observe a similar pattern of growth: China's total imports increased from \$80.6 billion in 1992 to \$1.96 trillion in 2014, while average imports per firm rose from \$3.59 million in 2000 to \$11.41 million in 2014. By the end of our sample period, China had become the world's largest exporter (with a 12.3% share of global merchandize trade), as well as the second largest importer (accounting for 10.3% of global merchandize trade).[7]

We are particularly interested in the operations of firms that are involved in manufacturing value chains. We therefore focus eventually in our analysis on a subsample that removes wholesalers and retailers, as identified using a standard procedure in the literature that locates keywords related to trade intermediation in firm names (Ahn et al., 2011). During 2000–2014, the

[4] This relates to an older literature on double marginalization in pricing decisions.

[5] The trade flows in the Chinese customs datasets span different vintages of HS codes. Where necessary, we have used concordance tables provided by the United Nations Statistical Division to perform crosswalks across different vintages of the HS 6-digit product codes, before mapping them into the industries in the 2007 Chinese Input-Output Tables; see the Data Appendix for more details.

[6] The average annual growth of Chinese exports increased from 13.7% in 1992–2001 to 16.1% in 2001–2014. Similarly, the average annual growth of Chinese imports rose from 13.3% in 1992–2001 to 15.4% in 2001–2014.

[7] This is based on the value of total merchandize exports (respectively, imports) for each year computed from the CCTS, divided by the value of world merchandize trade from the World Development Indicators (WDI).

Table 1
Firm-level production and trade activity, summary statistics.

	CCTS 2000-2014			ASIF 1999-2007			ASIF-CCTS 2000-2006		
	N	Mean	St Dev	N	Mean	St Dev	N	Mean	St Dev
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: CCTS trade statistics									
All Traders	532,704 exporters, 422,818 importers								
Log Imports	1,628,806	12.05	2.96						
Log Exports	2,385,331	13.15	2.33						
Import upstreamness (U^M)	1,628,806	3.60	0.83						
Export upstreamness (U^X)	2,385,331	3.29	0.78						
Two-way Traders	259,439 firms						56,282 firms		
Log Imports	1,060,154	12.19	3.03				173,951	12.85	2.82
Log Exports	1,060,154	13.77	2.39				173,951	14.13	2.12
Import upstreamness (U^M)	1,060,154	3.68	0.76				173,951	3.70	0.75
Export upstreamness (U^X)	1,060,154	3.25	0.77				173,951	3.24	0.79
Import-Export Upstreamness (U^M - U^X)	1,060,154	0.42	0.89				173,951	0.46	0.89
Non-Ordinary Imports / Total Imports	1,060,154	0.55	0.46				173,951	0.71	0.41
Non-Ordinary Exports / Total Exports	1,060,154	0.39	0.45				173,951	0.52	0.44
Processing Imports / Total Imports	---	---	---				173,951	0.59	0.44
Processing Exports / Total Exports	---	---	---				173,951	0.52	0.44
Private Domestic Firm (PVT)	1,060,154	0.31	0.46				173,951	0.14	0.35
State-Owned Enterprise (SOE)	1,060,154	0.05	0.21				173,951	0.05	0.23
Joint Venture (JV)	1,060,154	0.20	0.40				173,951	0.35	0.48
Foreign-Owned MNC Affiliate (MNC)	1,060,154	0.44	0.50				173,951	0.46	0.50
Panel B: ASIF production statistics				541,745 firms					
Log Real Total Sales				1,703,955	9.90	1.35	171,325	10.78	1.41
Log Employment				1,875,361	4.72	1.15	173,951	5.49	1.17
Log Total Assets				1,871,630	9.64	1.43	173,875	10.66	1.48
Cap. intensity (Log net fixed assets / worker)				1,859,593	3.51	1.36	173,415	3.73	1.43
Skill intensity (Log average wage)				1,862,573	2.32	0.72	173,714	2.66	0.65
Log Real VA per Worker				1,612,143	3.94	1.29	165,955	4.04	1.21
Log TFPR OP				1,266,402	0.77	0.87	154,936	1.04	0.83
Log TFPR LP				1,641,138	4.30	1.23	154,936	7.16	1.39
Log TFPR ACF				1,266,402	3.47	1.43	1,54,936	3.62	1.27
Log (Age+1)				1,867,812	2.01	0.89	173,675	2.03	0.67
Log Real Value Added				1,612,143	8.66	1.51	165,955	9.54	1.54
Log Real Total Inputs				1,703,762	9.54	1.38	171,252	10.40	1.45
Net Fixed Assets / Total Assets				1,871,630	0.33	2.17	173,875	0.31	0.21
Inventories / Total Assets				1,871,630	0.19	0.17	173,875	0.21	0.16
Profits (Real)				1,717,353	3,193.09	49,029.37	171,487	10,196.97	119,999.19
Profits / Sales				1,703,955	0.05	2.33	171,325	0.07	5.32

Notes: Summary statistics are reported separately for the full CCTS 2000–2014 panel of non-intermediary firm-years (Columns 1–3); the full ASIF 1999–2007 panel of firms (Columns 4–6); and the baseline matched CCTS-ASIF 2000–2006 panel of non-intermediary firms, in all years in which the firm both imports and exports (Columns 7–9). All variables are as defined in the text.

intermediaries we identify constitute about 8% of all firms that conduct international trade; these account for 18.4% of China's exports and 19.9% of China's imports by value.

Columns 1–3 in Table 1 provide summary statistics for the sample of non-intermediary firms in the 2000–2014 panel. During this period, 532,704 firms pursued exporting and 422,818 firms pursued importing at least once, while 259,439 firms were two-way traders (i.e., reporting both exports and imports in the same year) in at least one year. We view the latter – the non-intermediary, two-way traders – as firms that are particularly likely to be engaged in global production chains. These firms generated log export revenues of 13.77 on average (standard deviation: 2.39), and their mean log imports stood at 12.19 (standard deviation: 3.03). The panel of two-way traders comprises 31% private domestic entities, 5% SOEs, 20% JVs, and 44% MNC affiliates. Of note, the share of private firms increased sizeably over time, from 6% in 2000 to 48% in 2014, at the expense of the share of SOEs and JVs. With regard to trade regimes, the average share of "non-ordinary" trade (i.e., processing plus "other" regimes) in firm exports and imports was 39% and 55%, respectively. (We report this non-ordinary trade share as the data do not distinguish between processing and "other" trade regimes between 2007 and 2014; we will later use the actual firm-level processing trade share when we run regressions on the subsample for 2000–2006 that we are able to merge with the manufacturing firm survey data.)

2.2. Production statistics

For information on the operations of Chinese firms, we draw on the Annual Survey of Industrial Firms (ASIF) conducted by China's National Bureau of Statistics, available for 1999–2007. The survey sample covers all state-owned enterprises (regardless of size), and private companies with sales above 5 million Chinese Yuan.[8] The ASIF contains information that would appear in a typical firm balance sheet. This includes variables that speak to: size (total sales), inputs (employment, average wage, intermediate input and material purchases), value added, asset structure (net fixed assets, inventories), and performance (profits). In addition, we extract from the ASIF each firm's age and main industry of activity (as classified under China's GB/T coding system). We use the data to construct several standard measures of firm productivity, namely log real value added per worker, as well as revenue-based TFP measures (TFPR) based on production function estimates following the methodologies of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). More specifically, to construct the TFPR measures, we draw directly on the ASIF for data on labor inputs (employment) and intermediate input purchases, while we follow Brandt et al. (2012) to compute a firm-level real capital stock series. The production function estimation is performed for each TFPR measure at the GB/T 2-digit industry level (30 categories). (Please see the Data Appendix for further details on the construction of the firm productivity measures.)

Our empirical analysis critically relies on combining firm-level trade and balance-sheet data from the CCTS and ASIF respectively. While each dataset is organized around company registration numbers, they do not share unique firm identifiers. Following standard practice in the literature, we merge the customs records with the industrial survey using an algorithm that matches firms' names and contact information, including addresses and phone numbers.[9] This procedure delivers a large and broadly representative sample. We focus on a baseline matched ASIF-CCTS sample spanning 2000–2006, during which the coverage of firms and key variables in the ASIF is at its best. For 2000–2006, we are able to obtain ASIF balance-sheet data for 30% of the firms in the CCTS; these firms mediate 51% of all exports and 43% of all imports recorded in the CCTS during these years. Conversely, we locate CCTS trade transactions for 52% of all ASIF firms with positive exports; these account for about 80% of the total export value reported in the ASIF balance sheets.

Columns 4–6 in Table 1 summarize the variation in firm size, inputs, productivity, and performance in the full ASIF panel for 1999–2007, for key measures that will feature in our regressions. At the same time, Columns 7–9 report the trade and production statistics for the matched ASIF-CCTS panel of non-intermediary firms that are two-way traders in 2000–2006. Overall, the matched firms tend to be larger and more productive than the average firm in the full ASIF panel, suggesting that the merge is capturing firms that account for the majority of economic activity in the ASIF. The matched firms also tend to exhibit larger import and export volumes than the full CCTS sample (Columns 1–3), though the average upstreamness of the firm-level trade flows (based on the upstreamness measures to be defined below) is very similar. (Appendix Table 1 reports unconditional two-way correlations among the key firm indicators of productivity, size, and experience.)

2.3. Industry upstreamness

We use Chinese Input-Output (IO) Tables and the methodology developed in Fally (2012) and Antràs et al. (2012) to construct a measure of the production line position of different industries. Conceptually, the upstreamness of industry i, U_i, is a weighted average of the number of stages from final demand at which i enters as an input in production processes. In an economy with $N \geq 1$ industries, we calculate U_i as follows:

$$U_i = 1 \cdot \frac{F_i}{Y_i} + 2 \cdot \frac{\sum_{j=1}^{N} d_{ij} F_j}{Y_i} + 3 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} d_{ik} d_{kj} F_j}{Y_i} + 4 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} d_{il} d_{lk} d_{kj} F_j}{Y_i} + \ldots, \tag{1}$$

where Y_i is gross output in industry i, and F_i is the value of that output that goes directly to final uses (i.e., consumption or investment). d_{ij} is the direct requirements coefficient in the Chinese IO Tables, this being the value of i used as an input to produce one yuan worth of industry j output.[10]

The formula in (1) assigns a weight of 1 to the share of industry-i output that goes directly to final use, a weight of 2 to the share that is channeled to final use through exactly one other industry, and so on. Though expressed as an infinite sum in (1), Antràs et al. (2012) show that U_i can be evaluated in a few succinct matrix algebra steps. In particular, let D denote the matrix of direct requirement coefficients, namely: the N-by-N matrix whose i-th row and j-th column is equal to d_{ij}. Likewise, define F to be a column vector whose i-th entry is F_i. The numerator of (1) is then exactly equal to the i-th entry of $[I - D]^{-2}F$, where

[8] This is equivalent to 0.6 million USD, based on the bilateral exchange rate in 2005. The ASIF data are cleaned following the steps in Wang and Yu (2012), to remove: (a) firms in non-manufacturing industries (i.e., retaining only firms with 2-digit GB/T industry code in 13–43); (b) observations with negative values for output, sales, exports, capital, total assets, total fixed assets, wages, or intermediate inputs, and observations with zero employees; and (c) observations with total assets less than total fixed assets or total liquid assets, or with total sales less than exports.

[9] See Wang and Yu (2012) for a detailed description of the matching procedure.

[10] Following Antràs et al. (2012), we scale d_{ij} by the factor $Y_i/(Y_i - X_i + M_i - NI_i)$, where $X_i - M_i$ is equal to the net exports of i, and NI_i is the net change in inventories of i reported in the IO Tables. This correction accounts for industry-i flows across country borders, as well as into and out of inventories; as Antràs et al. (2012) show, this is the correction term implied by a proportionality assumption, that these industry-i flows are used as inputs across industries j in the same proportion as what is observed in domestic cross-industry flows.

I is the N-by-N identity matrix. The denominator of (1), Y_i, is in turn equal to the i-th entry of $[I - D]^{-1}F$, which is the familiar Leontief inverse matrix formula for industry gross output.[11,12]

By construction, one can see from (1) that $U_i \geq 1$, with equality if and only if all of industry i's output goes directly to final use. If instead industry i tends to enter into production chains as an intermediate input multiple stages prior to final demand, this would be reflected in a larger value of U_i. For example, rubber can be used directly as a final product (one step to final consumers) or in the manufacture of tyres that are in turn assembled into cars that are then sold as a final product (three steps to final consumers). By contrast, apparel comprises mostly final goods (one step to final consumers) and rarely serves as an intermediate input to other sectors. Rubber would thus have a higher U_i value than apparel.

Table 2 reports summary statistics for U_i based on the 2007 China IO Tables, which contains a relatively detailed set of 135 industries. The measure of industry upstreamness ranges from 1 to 5.86, with a mean of 3.16 and a standard deviation of 1.12. As reported in the lower panel of the table, the 10 most upstream industries comprise mainly sectors involved in the extraction and processing of raw materials; on the other hand, the 10 least upstream industries include service sectors with a large share of direct sales to consumers. We will proceed to use these measures of industry upstreamness that have been benchmarked to the Chinese economy to describe the production line position of China-based firms. Note that we document similar trends when using the disaggregate US 2002 IO Tables (with 426 industries) as an alternative benchmark.

2.4. Firm production line position

We apply the above industry measure of upstreamness, U_i, to characterize the production line position of each firm in the CCTS. We compute a weighted-average upstreamness of firm f's imports (U_{ft}^M) and exports (U_{ft}^X), as well as the difference between the two ($U_{ft}^M - U_{ft}^X$), as follows:

$$U_{ft}^M = \sum_{i=1}^{N} \frac{M_{fit}}{M_{ft}} U_i, \qquad U_{ft}^X = \sum_{i=1}^{N} \frac{X_{fit}}{X_{ft}} U_i, \text{ and } \qquad U_{ft}^M - U_{ft}^X = \sum_{i=1}^{N} \left(\frac{M_{fit}}{M_{ft}} - \frac{X_{fit}}{X_{ft}} \right) U_i. \tag{2}$$

Since the CCTS reports trade flows by HS product, we use concordance tables between HS product codes and Chinese IO industry categories to obtain the value of each firm's exports (X_{fit}) and imports (M_{fit}) in IO industry i in year t. Note that $X_{ft} = \sum_{i=1}^{N} X_{fit}$ and $M_{ft} = \sum_{i=1}^{N} M_{fit}$ are firm f's total exports and imports respectively, so the weights in (2) are proportional to the export (respectively, import) share of each industry in the firm's overall trade profile.[13]

We interpret U_{ft}^M and U_{ft}^X as summary measures of the global production line position of the firm. In practice, global production processes can be structured in complex ways, with some portions featuring sequences of stages ("snakes"), while other segments might be set up in a manner resembling a hub-and-spoke ("spiders", in the lingo of Baldwin and Venables, 2013). The measures in (2) seek to capture how firms are situated within these production processes, even in the absence of granular information about how each firm is structuring and locating its specific operations. Instead, (2) taps on the rich Chinese customs data on firm-level imports and exports, and combines these with upstreamness measures for a relatively disaggregate set of industries, in order to infer – in an admittedly stylized manner – the average positioning of a firm's activities within GVCs relative to final demand. Particularly for non-intermediary firms that both import and export, one can view U_{ft}^M as capturing the average upstreamness of materials and inputs that are brought into China by the firm, and U_{ft}^X as reflecting the average upstreamness of the semi-finished or finished goods sold to buyers worldwide. We view the difference, $U_{ft}^M - U_{ft}^X$, as informative of the span of production stages that the firm oversees or coordinates within China; this could take the form of direct in-house production, but it does not exclude the possibility of outsourcing to other domestic suppliers.[14]

In Columns 1–3 of Table 1, we report summary statistics for U_{ft}^M, U_{ft}^X, and $U_{ft}^M - U_{ft}^X$, across firm-years with positive exports and imports in the CCTS 2000–2014 panel (restricted to non-intermediary firms only). The mean upstreamness of firm imports is 3.68, while the corresponding mean upstreamness of firm exports is 3.25, implying an average span of 0.42 production stages. There is significant dispersion around these means, with the standard deviations equal to 0.76, 0.77, and 0.89 respectively. As noted earlier, these metrics are very similar in the matched sample of non-intermediary two-way traders with both CCTS customs and ASIF production data (Columns 7–9).

[11] Fally (2012) and Antràs et al. (2012) moreover show that the upstreamness measure defined in (1) is the unique solution to the following recurrence relation:

$$U_i = 1 + \sum_{j=1}^{N} a_{ij} U_j,$$

where $a_{ij} = d_{ij}(Y_j/Y_i)$ is the share of industry-i's output that is sold to industry j. Intuitively, industry i can be viewed as being one stage more upstream than a weighted sum of the industries j that purchase i as an input.

[12] See also Miller and Termushoev (2017) and Antràs and Chor (2018) for a detailed exposition of the definition and construction of this upstreamness measure when extended to the context of multi-country IO tables, such as the World Input-Output Database (WIOD).

[13] In principle, one could use industry upstreamness values that vary by source country – calculated from the respective countries' IO Tables – when constructing the firm-level upstreamness measures in (2), in order to reflect potential differences across countries in local technological and production conditions. In practice, however, we do not pursue this approach as currently available cross-country datasets of IO Tables tend to feature harmonized industry categories that are relatively coarse, compared to the level of industry detail in the Chinese and US IO Tables. For what it is worth, Antràs et al. (2012) report a pervasive positive correlation between industry upstreamness values computed for different countries in the OECD STAN database; this features 41 industries, of which only 13 are in manufacturing.

[14] More generally, given the weighted-average nature of the firm-level upstreamness measures, there should be no presumption that all production steps that are between U_{ft}^M and U_{ft}^X stages from final demand are actually physically performed by the firm within China.

Table 2
Industry-level upstreamness, 2007 IO tables.

	25th	Median	75th	Mean	St Dev
Panel A: Industry upstreamness					
All 135 industries	2.343	3.060	3.950	3.161	1.118
Primary (IO industries: 1 to 10)	3.331	4.343	5.345	4.302	1.176
Manufacturing (IO industries: 11 to 91)	2.498	3.060	4.104	3.276	1.008
Services (IO industries: 92 to 135)	1.720	2.966	3.480	2.691	1.076
Panel B: Ten most and least upstream industries					
Nonferrous metal mining (IO9)		5.861			
Oil & gas exploration (IO7)		5.508			
Basic chemical raw materials (IO39)		5.375			
Coal mining & washing (IO6)		5.345			
Scrap waste (IO91)		5.256			
Chemical fiber (IO47)		5.162			
Ferrous metal mining (IO8)		5.114			
Coking (IO38)		5.095			
Pipeline transportation (IO101)		5.023			
Nonferrous metal alloying & smelting (IO61)		4.877			
–					
Resident services (IO124)		1.382			
Software (IO107)		1.275			
Convenience food (IO18)		1.269			
Health (IO127)		1.269			
Education (IO126)		1.212			
Public facilities management (IO123)		1.074			
Sports (IO133)		1.060			
Construction (IO95)		1.058			
Public administration & social organizations (IO135)		1.026			
Social welfare (IO129)		1.000			

Notes: Computed from Chinese Input-Output Tables for 2007.

Before proceeding, it is useful to note several caveats about U_{ft}^M and U_{ft}^X. While we observe the detailed product composition of a firm's exports, and can deduce the value of its domestic sales by subtracting its total exports from total sales (where available in the ASIF), we do not have data on the firm's domestic sales by product. An analogous comment applies on the input side, as we do not directly observe the product breakdown of a firm's material inputs in the ASIF. Thus, U_{ft}^M and U_{ft}^X should be seen as good reflections of the upstreamness of a firm's overall operations, only to the extent that these are well-represented by the product composition of the firm's imports and exports. Note further that the ASIF data do not provide information on whether the material inputs are being purchased through intra-firm or arm's length transactions. We are thus not able to draw sharp conclusions on the basis of this data about the extent to which vertical integration of the supply chain is being pursued relative to outsourcing.

3. China's global production line position

3.1. Aggregate trends

We start by examining key trends in China's global production line position at the aggregate level over the 1992–2014 period. We characterize this in each year by the weighted-average upstreamness of China's imports and exports, $U_{China,t}^M$ and $U_{China,t}^X$, as given by:

$$U_{China,t}^M = \sum_{i=1}^N \frac{M_{it}}{M_t} U_i, \quad \text{and} \qquad U_{China,t}^X = \sum_{i=1}^N \frac{X_{it}}{X_t} U_i. \tag{3}$$

Here, U_i is the industry upstreamness measure from (1) based on the 2007 China IO Tables; $\frac{M_{it}}{M_t}$ is the value of imports classified as being from industry i expressed as a share of China's total imports in year t, while $\frac{X_{it}}{X_t}$ is the industry-i export share. In practice, for 2000–2014, we compute (3) by taking a weighted average of the firm-level upstreamness measures defined earlier in (2) across all firms, where the weights are each firm's share in total Chinese imports (respectively, exports):

$$U_{China,t}^M = \sum_f \frac{M_{ft}}{M_t} U_{ft}^M, \quad \text{and} \qquad U_{China,t}^X = \sum_f \frac{X_{ft}}{X_t} U_{ft}^X. \tag{4}$$

It is straightforward to see that (4) is equivalent to (3), since $M_{it} = \sum_f M_{fit}$ and $X_{it} = \sum_f X_{fit}$.

We report the aggregate trends we uncover in a series of stylized facts:

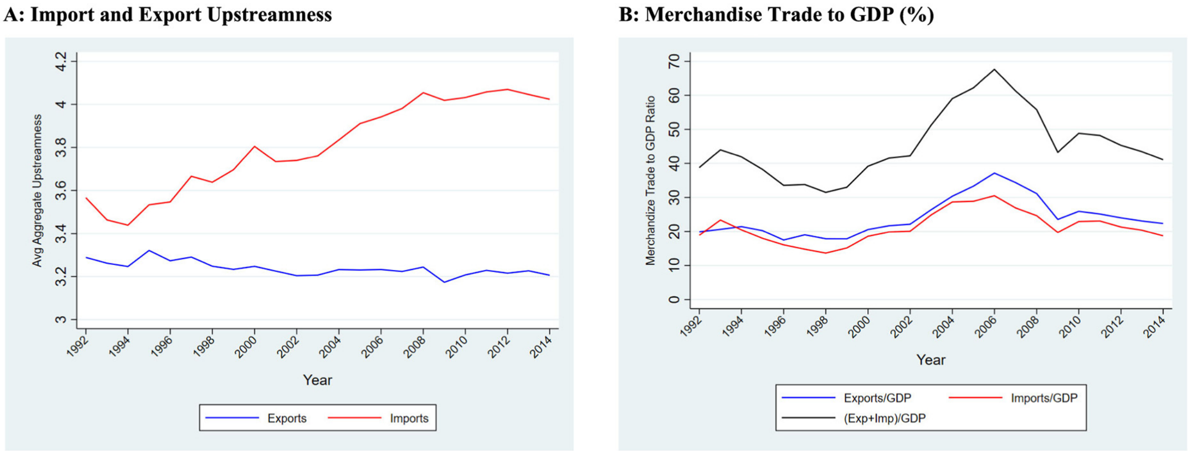

Fig. 1. Trends in China's aggregate trade and global production line position. Notes: Authors' own calculations based on Chinese Customs Trade Statistics. Aggregates are based on data at the province or city level for 1992–1999 and data at the firm level for 2000–2014. Information on China's GDP used in Panel B is from the World Development Indicators.

Macro Trend 1: *Over 1992–2014, Chinese imports became significantly more upstream, while Chinese exports became slightly more downstream, in relation to sources of final demand.*

Fig. 1A traces the evolution of $U^M_{China,t}$ and $U^X_{China,t}$ over the entire 23-year sample period. Two features stand out: First, Chinese imports are persistently more upstream than Chinese exports. This reflects the tendency for China-based firms to use imported inputs when producing goods that are then exported to foreign markets, and is consistent with – but not exclusively driven by – the important role that processing trade has played in the Chinese economy. Note that there is nothing that preordains that a country's imports will necessarily be more upstream on average than its exports. For example, countries rich in natural resources – and that export raw materials in exchange for imports of final goods – tend to exhibit the opposite pattern.[15]

Second, the production line position of China's exports remained fairly stable between 1992 and 2014, with a slight decline in $U^X_{China,t}$ from 3.29 to 3.21. By contrast, aggregate Chinese imports became dramatically more upstream, with $U^M_{China,t}$ rising from an initial value of 3.57 to 4.02. This latter rise was not driven simply by increased imports of agricultural or mineral commodities: When we re-compute (3) using only IO industries in manufacturing – with the weights being the corresponding share of manufacturing industry i in total manufacturing trade flows – we find that China's import upstreamness rose, albeit less sharply from 3.48 in 1992 to 3.74 in 2014 (see Appendix Fig. 1A); we obtain a similar pattern if we instead drop the entire section of HS codes for mineral products, i.e., Section V, HS 25–27, which includes petroleum products, when computing aggregate upstreamness (Appendix Fig. 1B). Separately, we have checked that the upward trend in $U^M_{China,t}$ was not due to China's increased purchases of capital goods and equipment from abroad: Dropping products classified as capital goods under the UN Broad Economic Categories (BEC) system, we still find that import upstreamness rose from 3.82 in 1992 to 4.12 in 2014 (Appendix Fig. 1C).[16] This "fanning out" pattern is moreover robust when $U^M_{China,t}$ and $U^X_{China,t}$ are constructed using industry upstreamness measures drawn from the 2002 US IO tables (Antràs et al., 2012), in place of the U_i measures from the 2007 Chinese IO tables (Appendix Fig. 1D).[17]

Fig. 1A suggests that over time, Chinese firms have either developed the capability and/or found it profitable to perform more upstream stages of production processes, so that they have come to span wider segments of GVCs. This is broadly consistent with the observation that the domestic value added embedded in Chinese exports has been rising over time (Kee and Tang, 2016), to the extent that spanning more stages implies a greater use of Chinese factors of production. The rise in China's import upstreamness was moreover concentrated in the period prior to 2008, and tapered off subsequently. This is noteworthy, as it coincides with the onset of a slowdown in the growth rate of Chinese trade relative to its GDP. As Fig. 1B illustrates, the ratio of China's merchandize trade (exports plus imports) to GDP increased sharply following China's WTO accession in 2001, reaching about 70% in 2006.[18] The years since have seen a decline in this ratio that has persisted past the end of the Global Financial Crisis,

[15] Using trade data from 2002, Chor (2014) reports that the weighted-average upstreamness of imports was lower than that of exports for such resource-rich countries as Australia, New Zealand, and Brunei.

[16] Appendix Table 2 lists the 20 HS products that experienced the fastest import growth rates between 2002 and 2006, among the subset of products with above-median upstreamness values. This list features a mix of agriculture-related products (e.g., Buckwheat, Fertilizers), minerals (e.g., Ethylene, Liquefied natural gas), and intermediate inputs in manufacturing (e.g., Coir yarn, Hot-rolled bars and rods), suggesting that none of these broad categories of products was responsible on its own for the overall rise in the upstreamness of China's imports. Note that we focus on 2002–2006, as product codes are consistently recorded in the 2002 HS vintage during these years; this period also coincides with the bulk of the rise in aggregate import upstreamness.

[17] The mean upstreamness value across industries in the 2002 US IO Tables is 2.09, lower than that in the 2007 Chinese IO Tables. This accounts for the lower values reflected on the vertical axes in Appendix Figure 1D.

[18] The value of China's aggregate merchandize trade is calculated directly from the customs data, while the data on China's GDP in current US dollars is from the World Development Indicators.

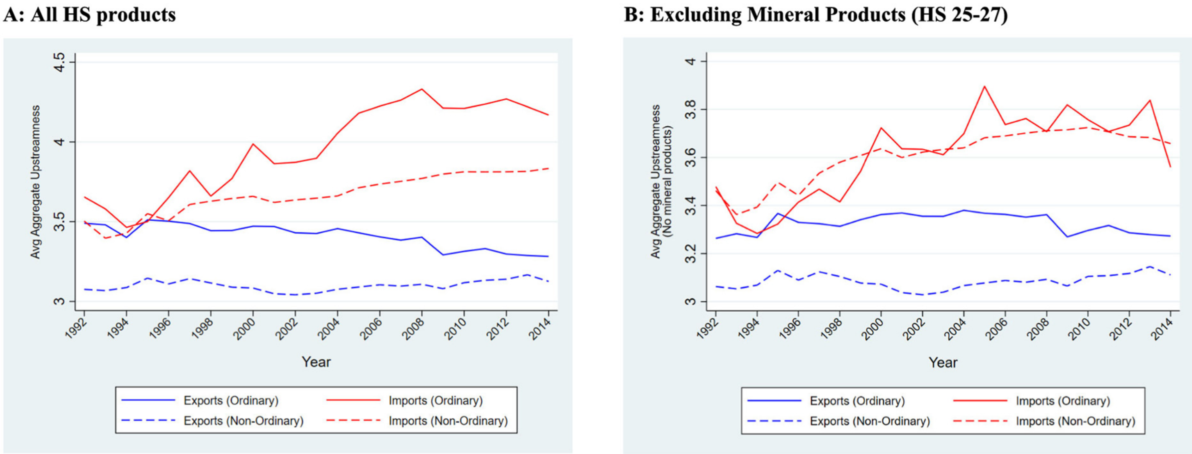

Fig. 2. Trends in aggregate upstreamness by customs trade regime. Notes: Authors' own calculations based on Chinese Customs Trade Statistics. Aggregates are based on the trade regime status of each trade transaction. Non-ordinary trade flows combine processing and "other" trade regimes.

prompting observers to label this as a structural break in the manner of China's engagement in international trade. This has been attributed (among other causes) to the rebalancing of China's economy towards domestic demand, or a possible peaking out in supply chain offshoring from developed countries to China (IMF, 2016; Frankel, 2016). What our first *Macro Trend* indicates is that these broader economic developments were accompanied by a steadying in the global production line position of China's imports (and exports).

We have found the above "fanning out pattern" of Chinese import and export upstreamness to be present in various subsample cuts of the customs data. Fig. 2A plots the weighted-average upstreamness of Chinese trade flows, separately for non-ordinary trade (dashed lines) and ordinary trade (solid lines). The pattern we observe for ordinary trade mirrors closely that for aggregate trade flows seen in Fig. 1A: Ordinary exports and imports had similar upstreamness values at the start of the sample period, but ordinary imports became almost a full production stage more upstream than ordinary exports by 2014. Along with this, the upstreamness of ordinary imports into China rose more sharply than that of imports brought in under non-ordinary trade regimes. That said, this gap can be attributed largely to imports of mineral products (which tend to have high U_i values), as the upstreamness of ordinary imports falls back in line with that of non-ordinary imports once HS codes 25–27 are excluded (Fig. 2B).[19]

Fig. 3A performs a similar exercise looking across firms by ownership types. There is a clear and stable ranking with the imports and exports of state-owned enterprises (SOE, solid lines) systematically more upstream than the corresponding trade flows of private domestic firms (PVT, dashed lines), which in turn are more upstream than those of joint ventures and fully-owned multinational affiliates (JV/MNC, dot-dashed lines). Over time, there has been an increase in the import upstreamness of all three firm types, with the climb most distinct for SOEs. As Fig. 3B shows though, this gap between the import upstreamness of SOEs and other firms is reduced when one removes mineral products (HS codes 25–27). This is consistent with the increased role that SOEs have played in securing imports of mineral resources as inputs for China's industrial activities.[20]

3.2. From aggregate to firm upstreamness

The above trends in the evolution of China's export and import upstreamness can arise from changes among continuing firms and/or changes in the set of active trading firms. This motivates us to undertake a decomposition of the observed changes in $U^M_{China,t}$ and $U^X_{China,t}$ over time, to better understand the firm-level sources of these aggregate shifts.

Using (4), the change in $U^M_{China,t}$ between time $t-1$ and t can be expressed as:

$$\begin{aligned}\Delta U^M_{China,t} = &\sum_{f \in EN^M_t} \frac{M_{ft}}{M_t} U^M_{ft} - \sum_{f \in EX^M_t} \frac{M_{f,t-1}}{M_{t-1}} U^M_{f,t-1} \\ &+ \sum_{f \in C^M_t} \frac{M_{f,t-1}}{M_{t-1}} \Delta U^M_{ft} + \sum_{f \in C^M_t} \left(\frac{M_{ft}}{M_t} - \frac{M_{f,t-1}}{M_{t-1}} \right) U^M_{ft},\end{aligned} \tag{5}$$

[19] We have also compared the global production line positioning of firms classified as trade intermediaries versus non-intermediaries in Appendix Figure 2A. The pattern exhibited across these two subsets of firms was similar, with a clear rise in import upstreamness over the sample period, even while export upstreamness remained stable. Separately, Appendix Figure 2B points to a similar trend of rising import upstreamness, albeit slightly less pronounced, even when we focus just on the non-intermediary firms that are in our merged ASIF-CCTS sample for 2000–2006.

[20] Li et al. (2015) document how the monopoly power of China's state-owned enterprises in upstream raw materials industries has expanded over time, including in petrochemicals and electricity generation.

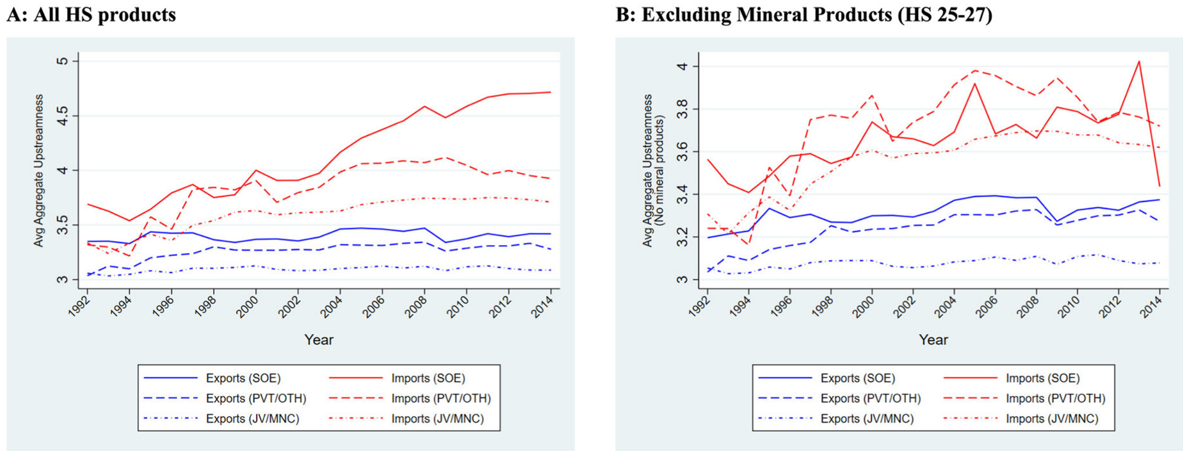

Fig. 3. Trends in Aggregate Upstreamness by Firm Ownership Type. Notes: Authors' own calculations based on Chinese Customs Trade Statistics. Ownership type is deduced from the sixth digit of CCTS firm codes: "SOE" = state-owned enterprises, "PVT/OTH" = private and all other enterprises, "JV/MNC" = joint venture and multinational companies.

where the firms f have been exactly partitioned into three subsets: (i) those that report imports in both year $t-1$ and t, C_t^M ("continuers"); (ii) those that do not report imports in year $t-1$, but do so in year t, EN_t^M ("entrants"); and (iii) those that report imports in year $t-1$, but not in year t, EX_t^M ("exiters"). The terms in the first line of (5) are changes in aggregate import upstreamness attributed to the extensive margin under this decomposition, due to firms that commence importing ($\sum_{f \in EN_t^M} \frac{M_{ft}}{M_t} U_{ft}^M$) and those that cease to do so ($-\sum_{f \in EX_t^M} \frac{M_{f,t-1}}{M_{t-1}} U_{f,t-1}^M$); to be clear, these capture instances of entry into or exit from importing, which need not be episodes of entry into or exit from production entirely. The terms on the second line of (5) stem in turn from the intensive margin. Here, $\sum_{f \in C_t^M} \frac{M_{f,t-1}}{M_{t-1}} \Delta U_{ft}^M$ reflects the contribution of *within*-firm changes in upstreamness over time – which arise from changes in the mix of products a firm imports – holding the firm import weights constant at their initial level. The remaining term, $\sum_{f \in C_t^M} \left(\frac{M_{ft}}{M_t} - \frac{M_{f,t-1}}{M_{t-1}} \right) U_{ft}^M$, picks up the role of shifts *across* continuing firms in each firm f's importance as an importer. An analogous formula to (5) holds on the exporting side.

Implementing (5) on the full CCTS firm-level panel, we obtain:

Macro Trend 2: *Over the 2000–2014 period, the rise in China's aggregate import upstreamness stems from: (i) the entry of firms whose imports are more upstream on average than exiting firms; and (ii) a rise in import upstreamness within continuing firms. The modest decrease in China's aggregate export upstreamness reflects both changes within and reallocations across continuing firms.*

Table 3 summarizes the main findings from this decomposition exercise. We report the changes separately for 2000–2006 and for 2006–2014, bearing in mind that 2006 was when China's trade-to-GDP ratio reached its peak (Fig. 1B). Note that the additive nature of the decomposition means that we can simply add up the year-to-year changes corresponding to each term in (5) to obtain the contributions of each respective term over an extended period. Focusing first on import flows, the overall increase in $U_{China,t}^M$ during 2000–2006 (+0.137) is explained by two forces: the net extensive margin (+0.734), which implies new importers were shipping more upstream products into China than exiting importers; and the within-firm intensive margin (+0.190), so that the product mix of imports was also becoming more upstream for continuing importers.[21] These effects are offset to some extent by the negative cross-firm term on the intensive margin (−0.788), as most individual firms saw their shares in China's total imports fall during this period. Turning to the export side, we find that the modest fall in $U_{China,t}^X$ between 2000 and 2006 (−0.015) is accounted for by within-firm shifts (−0.009) and cross-firm changes (−0.793) among continuing exporters (i.e., both terms on the intensive margin), the latter in particular reflecting how individual firms were in general becoming smaller as a share of China's total exports during this period of rapid export growth. The pattern of these changes for $U_{China,t}^M$ and $U_{China,t}^X$ respectively are qualitatively similar prior to and after 2006, though they taper off in magnitude in the later period.

The findings from Table 3 indicate that the within-firm changes on the intensive margin resemble the broader "fanning out" pattern seen for China's aggregate trade flows (from Fig. 1A), with a clear rise in import upstreamness and a modest decline in export upstreamness over time. We shed further light on these within-firm shifts with:

[21] We have briefly explored how much of this extensive margin adjustment can be attributed to firm entry into production (rather than entry into importing per se). To address this, we restrict ourselves to the ASIF-CCTS merged sample from 2000 to 2006, since the information on a firm's year of establishment is only available in the ASIF. In the ASIF-CCTS, the change in aggregate import upstreamness accounted for by firm entry into importing is +1.028. Of this, the change which coincides with firm entry into production is +0.199, or about one-fifth of the overall shift. (We do not explore a decomposition on the exit margin, as the ASIF does not contain a shutdown date variable.)

Table 3
Decomposition of changes over time in aggregate upstreamness.

	Extensive Margin			Intensive Margin			Overall Change
	Firm Entry	Firm Exit	Net	Change in Firm U	Change in Firm Shares	Net	
$\Delta U^{M}_{China,t}$							
2000–2006	1.220	−0.486	0.734	0.190	−0.788	−0.597	0.137
2006–2014	1.368	−0.856	0.512	0.094	−0.524	−0.430	0.082
$\Delta U^{X}_{China,t}$							
2000–2006	1.189	−0.402	0.787	−0.009	−0.793	−0.802	−0.015
2006–2014	1.622	−0.894	0.727	−0.022	−0.732	−0.754	−0.026
$\Delta U^{M}_{China,t}$-$\Delta U^{X}_{China,t}$							
2000–2006	0.031	−0.084	−0.053	0.199	0.005	0.204	0.151
2006–2014	−0.254	0.038	−0.215	0.116	0.208	0.324	0.109

Notes: Based on the exact decomposition of changes in aggregate upstreamness, presented in eq. (5). The "net" extensive margin column sums up the contributions from firm entry and firm exit in the preceding two columns. The "net" intensive margin is the sum of the contributions in the preceding two columns stemming from: (i) changes in firm-level upstreamness, holding constant initial firm trade share weights; and (ii) changes in the firm trade share weights, holding constant firm-level upstreamness. The "Overall change" column is the sum of the net extensive and net intensive margin contributions. Firm entry and firm exit refer specifically to entry/exit from importing/exporting, which may occur even when the firm does not enter/exit from production.

Macro Trend 3: *Within firms over time, imports became significantly more upstream, exports became moderately more proximate to final demand, and the implied span of production stages performed within China increased during 2000–2014.*

We uncover this trend by estimating variants of the following firm-level regression specification:

$$\left\{U^{M}_{ft}, U^{X}_{ft}, U^{M}_{ft} - U^{X}_{ft}\right\} = \alpha + \sum\nolimits_{t=2001}^{2014} \alpha_t YEAR_t + \varphi_f + \varepsilon_{ft}. \tag{6}$$

The outcome variable is in turn the average upstreamness of a firm's imports (U^{M}_{ft}), the average upstreamness of a firm's exports (U^{X}_{ft}), and the difference between these two ($U^{M}_{ft} - U^{X}_{ft}$), as defined earlier in (2). We quantify common time trends in firms' global production line position by estimating coefficients α_t for a full set of year dummies $YEAR_t$, conditional on firm fixed effects, φ_f. The α_t's for $2001 \le t \le 2014$ thus capture average cumulative changes (relative to 2000) based on all firms that are active in year t. We conservatively cluster the standard errors by firm, to account for possible correlated shocks within firms over time in the ε_{ft} error terms.[22]

In Columns 1–2 of Table 4, we estimate (6) for U^{M}_{ft} and U^{X}_{ft} respectively using the full CCTS panel for 2000–2014. Columns 3–4 run these same regressions after excluding trade intermediaries, given that the import and export flows of these companies are often not tied to actual production decisions made by these firms. In both the full CCTS sample and the non-intermediary subsample, we find that the export upstreamness of firms declined steadily but moderately between 2000 and 2014, while the upstreamness of their imports rose quickly. The point estimates for the α_t's are significant across these four columns for almost all years, and typically rise in absolute value over time.

In the rest of Table 4, we further restrict the sample to non-intermediary firm-year observations that record a positive volume of both exports and imports, these being firms most likely to be engaged in GVCs. The import upstreamness of these non-intermediary two-way traders also increased dramatically during 2000–2014 (Column 5). On the other hand, their exports became only slightly more proximate to final demand; this trend tapered off after 2009, so that by 2014, the average level of firms' export upstreamness was not statistically distinguishable from that in 2000 (see the point estimate of α_{2014} in Column 6). For a representative firm, the cumulative changes in U^{M}_{ft} and U^{X}_{ft} over this period were 0.1992 and 0.0001 respectively, from average starting levels of 3.6961 and 3.2119 in 2000. As a result, the gap between the upstreamness of firms' imports and exports widened, implying an expansion in the span of stages performed within China of 0.1991 on average, or more than 41% up from the initial average value of $U^{M}_{ft} - U^{X}_{ft}$ of 0.4842 (Column 7).[23] In Appendix Table 3, we show that these trends in firms' production line position are robust even when we control for the number of HS 6-digit products that the firm imports and/or the number of HS 6-digit products that it exports in each year. There is a modest reduction in the α_t point estimates, but these still imply a cumulative average change in the span of stages, $U^{M}_{ft} - U^{X}_{ft}$, of 0.1594. This suggests that the expansion along the production chain within firms reflects the shifting of production steps into China, rather than changes in input and output product scope per se.[24]

Fig. 4 illustrates these within-firm changes over time in the span of stages performed in China, through several kernel density plots of $U^{M}_{ft} - U^{X}_{ft}$. We focus on the set of all non-intermediary firms that were two-way traders throughout the entire duration of our sample period; we refer to these firms in Fig. 4 as "survivors" . These firms tend to span more production stages as they age, as can be seen from the rightward shift in the distribution of $U^{M}_{ft} - U^{X}_{ft}$ for "survivors" between 2000 and 2014. One can compare

[22] All regression results in the paper are unaffected if we instead use heteroskedasticity-robust (but unclustered) standard errors.

[23] We obtain very similar results if we were to restrict the regressions to the subsample of non-intermediary firms that were "two-way traders" in *every* year between 2000 and 2014, or in every year between 2000 and 2006 (available on request).

[24] The estimates from Appendix Table 3 indicate that importing further upstream is associated with a smaller number of imported HS6 products. At the same time, firms whose exports are more proximate to final demand (i.e., are less upstream) tend to export more products. However, the implied economic magnitude of each additional imported (respectively, exported) product on firms' production staging is relatively small.

Table 4
Chinese firms' global production line position over time.

	Full Sample		All Non-intermediaries		Two-Way Non-intermediaries		
Dep variable	U^M_{ft} (1)	U^X_{ft} (2)	U^M_{ft} (3)	U^X_{ft} (4)	U^M_{ft} (5)	U^X_{ft} (6)	U^M_{ft} - U^X_{ft} (7)
Constant	3.4602***	3.3053***	3.4209***	3.2981***	3.5512***	3.2522***	0.2990***
Year 2001	−0.0025	−0.0009	0.0004	−0.0006	−0.0009	−0.0005	−0.0004
Year 2002	0.0053	−0.0005	0.0114***	0.0020	0.0032	0.0013	0.0019
Year 2003	0.0476***	−0.0027	0.0603***	0.0009	0.0332***	−0.0004	0.0337***
Year 2004	0.0842***	−0.0019	0.0967***	−0.0010	0.0617***	−0.0018	0.0635***
Year 2005	0.1237***	−0.0028	0.1408***	−0.0018	0.0898***	−0.0043*	0.0940***
Year 2006	0.1454***	−0.0091***	0.1680***	−0.0044**	0.1088***	−0.0045*	0.1133***
Year 2007	0.1864***	−0.0103***	0.2161***	−0.0101***	0.1526***	−0.0004	0.1530***
Year 2008	0.2028***	−0.0168***	0.2382***	−0.0162***	0.1708***	−0.0098***	0.1806***
Year 2009	0.2225***	−0.0161***	0.2626***	−0.0151***	0.1902***	−0.0086***	0.1987***
Year 2010	0.2151***	−0.0155***	0.2566***	−0.0146***	0.1809***	−0.0044	0.1853***
Year 2011	0.2151***	−0.0132***	0.2578***	−0.0124***	0.1798***	−0.0034	0.1832***
Year 2012	0.2360***	−0.0082***	0.2807***	−0.0065***	0.1924***	0.0021	0.1904***
Year 2013	0.2400***	−0.0073***	0.2862***	−0.0061***	0.1963***	0.0037	0.1926***
Year 2014	0.2414***	−0.0111***	0.2876***	−0.0102***	0.1992***	0.0001	0.1991***
Firm FE	Y	Y	Y	Y	Y	Y	Y
N	1,705,235	2,575,655	1,491,871	2,269,604	982,737	982,737	982,737
R^2	0.7328	0.8798	0.7432	0.8931	0.7163	0.9029	0.7276

Notes: The sample comprises different subsets of firm-year observations in the 2000–2014 CCTS panel; the “Two-Way Non-intermediaries” subsample in Columns 5–7 comprises all non-intermediary firms, in all years in which the firm both imports and exports. All regressions include firm fixed effects. Standard errors are clustered by firm; these are not reported in the table for brevity (available on request). ***, **, and * denote significance at the 1%, 5%, and 10% levels.

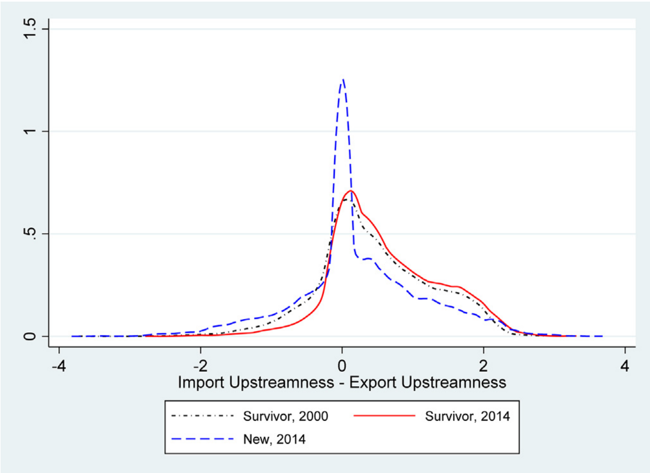

Fig. 4. Patterns in Firm Upstreamness: “Survivors” vs. “New” Two-Way Traders. Notes: Authors' own calculations based on Chinese Customs Trade Statistics. Kernel density plots of the difference between import and export upstreamness at the firm level. The sample comprises 5646 “survivor” firms that export and import in each year in 2000–2014, and 26,450 “new” two-way traders that reported export and import activity in 2014 but not in 2013.

these “survivors” in 2014 against firms that were “new” two-way traders in 2014, these being non-intermediary firms that both export and import in 2014 but not in 2013. The kernel density plot of $U^M_{ft} - U^X_{ft}$ for the new two-way traders is concentrated more tightly around its peak value, confirming that these firms tend to perform a narrower span of production stages than firms that have continuously been two-way traders for many prior years.[25]

Together, the patterns in Fig. 4 and Table 4 suggest that Chinese firms that are new to importing or exporting typically begin by conducting fewer production steps than existing traders, and then gradually expand the scope of their production stages as they survive and grow. We pick up on this theme in the next section, with a more detailed firm-level empirical analysis.

[25] We performed a Kolgomorov-Smirnov test to compare the distributions of $U^M_{ft} - U^X_{ft}$ for: (i) “survivors” in 2000 against “survivors” in 2014; and (ii) “survivors” in 2014 against “new” two-way traders in 2014. All tests comfortably rejected the null hypothesis of identical distributions, with p-values smaller than 0.0001. We obtain virtually identical findings if we were to alternatively define non-intermediary firms that were two-way traders in both 2000 and 2014 (but not necessarily in all years in between) to be “survivors”, and non-intermediary firms that were two-way traders in 2014, but not in 2000, to be “new” two-way traders (Appendix Figure 3). We also provide kernel density plots of the distributions for U^M_{ft} and U^X_{ft} separately (Appendix Figure 4). These reveal that the shift over time in $U^M_{ft} - U^X_{ft}$ for “survivors” is driven by their imports becoming more upstream.

4. Firm lifecycle facts

4.1. Estimation approach

We examine how the global production line position of Chinese firms evolves over time with their operations and performance using data from the matched ASIF-CCTS panel. We first analyze how productivity, size and experience correlate with import and export upstreamness at the firm level. Second, we document how firms' global production line position varies with the structure of firms' inputs, costs, assets, and profits.

Our goal is twofold. On the one hand, we want to agnostically establish novel and robust stylized facts that paint a coherent picture of how key firm attributes and performance metrics co-evolve with the global production line position of Chinese firms. At the same time, we also aim to inform the determinants and consequences of firms' participation in GVCs, and to offer a conceptual framework that can rationalize the empirical patterns through the lens of profit maximization. In Section 5, we will interpret the first set of results in terms of drivers of firms' production line position, and the second set of results in terms of its correlates and outcomes.

We explore the variation within firms over time with the following specifications:

$$\left\{U^M_{ft}, U^X_{ft}, U^M_{ft} - U^X_{ft}\right\} = \alpha + \beta Z_{ft} + \Gamma\Omega_{ft} + \varphi_f + \varphi_{st} + \varepsilon_{ft}, \text{ and} \tag{7}$$

$$\left\{Y_{ft}, \Pi_{ft}\right\} = \alpha + \beta\left\{U^M_{ft}, U^X_{ft}, U^M_{ft} - U^X_{ft}\right\} + \Gamma\Omega_{ft} + \varphi_f + \varphi_{st} + \varepsilon_{ft}. \tag{8}$$

In regression (7), the outcome variable is in turn one of the three measures of firms' participation in GVCs: the average upstreamness of firm imports, U^M_{ft}, the average upstreamness of firm exports, U^X_{ft}, and the difference between these two, $U^M_{ft} - U^X_{ft}$. The main variables of interest on the right-hand side, Z_{ft}, will be measures of firm productivity, size, and experience, which we view as potential drivers of a firm's decision over the span of stages to be engaged in. Our baseline findings presented in Section 4.2.1 come from estimating (7) via ordinary least squares (OLS). We also report results in Section 4.2.2 where we adopt an instrumental variable for firm productivity, constructed as a predicted foreign demand shock that a firm is plausibly exposed to.

In regression (8), we instead examine how various aspects of a firm's operations, Y_{ft} – pertaining to value added, input purchases, costs incurred, and asset structure – correlate with its global production line position (Section 4.3). We also consider how performance metrics related to firm profits, Π_{ft}, vary with $U^M_{ft} - U^X_{ft}$. We view the Y_{ft} and Π_{ft} on the left-hand side of (8) to be variables that are either decided upon jointly with a firm's choice over its span of production stages (such as input purchases) or outcomes of that decision (such as profits). The results we present for (8) are OLS estimates, so these should be viewed as informative partial correlations of how these features of the firm move in tandem with its span of stages.

In both (7) and (8), we absorb permanent observed and unobserved firm characteristics with firm fixed effects, φ_f. Likewise, we control for sector-specific supply and demand shocks with sector-by-year dummies, φ_{st}, where s denotes the GB/T 4-digit industry (up to 480 categories) of firm f's primary activity as designated in the ASIF. We include also several time-varying firm characteristics, Ω_{ft}, namely physical and human capital intensity, proxied respectively by log net fixed assets per worker and the log average wage; all results are robust to omitting these controls for factor intensities, and their inclusion has minimal effect on the coefficient estimates of interest. For each firm characteristic in Z_{ft}, Y_{ft} and Π_{ft}, we drop the tail 1% of observations across firms (at both tails) from the regression sample given the skew that is often present in these variables.[26] All standard errors are clustered by firm to allow for correlated shocks within firms over time.

The φ_f's account for intransient variation in institutional and market conditions across firm locations (i.e., Chinese cities, or special economic zones), such as labor costs, capital availability, infrastructure, and contract enforcement. These further subsume any such differences across firm ownership types. Since the φ_f's capture firms' primary industry of activity, they also control for systematic cross-sector differences in available production techniques and factor intensities, while the φ_{st}'s control flexibly for potential time trends in these sector-level forces.

The coefficient of interest, β, is therefore identified from the variation within firms over time, and reflects how changes in their supply chain position are associated with changes in their attributes and outcomes. Relating this back to the decomposition in Table 3, this is the variation captured by the intensive margin term that focuses on within-firm changes in U^M_{ft} and U^X_{ft}. We work primarily with these within-firm specifications, as these allow us to include a relatively thorough set of fixed effects to absorb potential omitted variables. (We also briefly present some results from a specification that instead teases out patterns in the variation across firms; see Appendix Table 6.)

We report results from running (7) and (8), when using firms in the matched ASIF-CCTS panel that are non-intermediary two-way traders.[27] The sample has about 175,000 observations, smaller than the roughly 1,000,000 firm-year observations available for the same category of firms in the 2000–2014 CCTS panel (Columns 5–7, Table 4). Recall that this is because the ASIF data spans a shorter time period, and the firm match between the CCTS and the ASIF is comprehensive but incomplete. Importantly,

[26] For example, we drop firms with a log real value added per worker smaller than its 1st percentile and larger than its 99th percentile when exploring the correlation of this productivity variable with firm-level upstreamness. The results are similar if we winsorize, rather than censor, the tail 1% values for each variable.

[27] The two-way non-intermediaries account for more than 92% of both the export and import value recorded for the firms that are in the matched ASIF-CCTS sample.

this restriction in sample size does not appear to affect our qualitative findings. For example, restricting the sample to ASIF-CCTS matched firms in 2000–2006 does not affect the conclusions drawn from the regressions that otherwise use the full 2000–2014 CCTS panel (e.g., from Table 4). We have also confirmed that all results hold when we broaden the ASIF-CCTS sample by relaxing the condition that a firm be a two-way trader (available on request). We document the findings that follow as a series of *Firm Facts*.

4.2. Firm productivity, size and experience

We first provide evidence that firms' global production line position evolved systematically with their productivity, size and experience during this period of rapid trade liberalization for China. We estimate (7) using various measures of these three firm attributes as the variable of interest, Z_{ft}.

Firm Fact 1: *When firms become more productive, bigger, or more experienced, their imports become significantly more upstream, their exports become moderately more proximate to final demand, and they span more production stages (in China).*

As noted earlier in Section 2.4, these empirical findings do not directly reveal whether the expansion along global production lines occurred through firms performing more manufacturing stages themselves or through the sourcing of previously imported inputs (i.e., previously offshored stages) from other domestic suppliers. This is because the ASIF data do not provide a detailed product-level breakdown of the material inputs that the firm purchases, nor the source – whether domestic or foreign – of these inputs. That said, these results do indicate that firms are taking responsibility for the supervision and completion of a wider segment of the supply chain within China, regardless of how that is operationalized. Our later findings in Section 4.3 for firms' value added, inputs and cost structure will also suggest that firms themselves are performing at least some of these additional production steps in-house.

4.2.1. OLS correlation

We begin with the role of firm productivity in Table 5. We find consistent patterns using several standard revenue-based measures of productivity in the literature, which we can readily construct from the ASIF.[28] In Panel A, we consider log real value added per worker, computed as the difference between output value and intermediate inputs, after deflating respectively by output and input deflators specific to the firm's primary GB/T 4-digit industry. In Panels B—D, we apply respectively the Olley-Pakes (OP), Levinsohn-Petrin (LP), and Ackerberg-Caves-Frazer (ACF) methodologies to obtain TFPR residuals from a production function estimated separately for each GB/T 2-digit industry. We arrive at similar findings and conclusions if we were to allow for more flexibility, by estimating separate production functions for firms under the three broad ownership categories (SOE, PVT, JV/MNC) within each GB/T 2-digit industry.

We document in each Panel in Table 5 that within firms over time, higher productivity is associated with significantly more upstream imports (a higher U^M_{ft}, Column 1) and with a stable profile in the proximity of exports to final demand (no significant change in U^X_{ft}, Column 2). As a result, productivity improvements are accompanied by firms managing a wider span of stages within China (an increase in $U^M_{ft} - U^X_{ft}$, Column 3). Moreover, the widening of the span of stages is not driven by where along the production chain firms operate: We continue to obtain a positive and significant correlation between firm productivity and $U^M_{ft} - U^X_{ft}$, with the coefficient estimate being largely unchanged, when we further condition on the GVC position of the firm's exports, U^X_{ft}, in Column 4.

It is useful to translate the coefficients in Table 5 into implied magnitudes for the span of stages that firms undertake in China. Bearing in mind the within-firm nature of the regression specification, we take the annualized change in each firm's productivity over time (calculated based on the first and final years in which the firm was active in the ASIF-CCTS panel), and consider the mean value of these within-firm changes as a benchmark shift in productivity. With this hypothetical shift, the implied change in the span of stages, $U^M_{ft} - U^X_{ft}$, ranges from 0.001 (for log TFPR OP) to 0.003 (for log TFPR LP).[29] This should be viewed against the average annual within-firm change in $U^M_{ft} - U^X_{ft}$ of 0.029 in the data. While it appears that within-firm productivity changes only account for modest shifts in the span of production stages, note that we will obtain much larger effects when we turn to the IV estimates in Section 4.2.2.

We examine in Table 6 the role of firm size and experience, which are firm attributes often closely linked to productivity. In Panel A, we use log total nominal sales as a comprehensive measure of firm scale.[30] As an alternative in Panel B, we consider log employment as a quantity-based indicator of production scale. Across both measures of firm size, we consistently observe that as firms grow bigger, they import inputs that are further upstream (Column 1), and shift exports towards products that are more proximate to the end-user (Column 2). These patterns contribute to the span of production stages $U^M_{ft} - U^X_{ft}$ widening significantly with firm size, regardless of whether or not one conditions on where along the supply chain the firm is anchored as proxied by U^X_{ft} (Columns 3 and 4).[31]

[28] We focus on TFPR, as the ASIF does not include information on input and output prices at the level of individual firms to allow the construction of reliable quantity-based measures of productivity (TFPQ). All price deflators that we have used in the data work are instead industry-level series.

[29] As an example, the mean annual within-firm change in log TFPR LP in Panel C is 0.198, so the associated change in the span of stages is: $0.0138 \times 0.198 \approx 0.003$.

[30] As (7) includes industry-year fixed effects, and output deflators are only available at the industry level, we would obtain equivalent results if the dependent variable were instead log real sales.

[31] In Appendix Table 4, Panel A, we report a similar set of correlations when we proxy for firm size using its log current total (worldwide) exports as reported in the CCTS customs records.

Table 5
Firm productivity and global production line position.

Dep variable:	U^M_{ft} (1)	U^X_{ft} (2)	U^M_{ft} - U^X_{ft} (3)	U^M_{ft} - U^X_{ft} (4)	U^M_{ft} (1)	U^X_{ft} (2)	U^M_{ft} - U^X_{ft} (3)	U^M_{ft} - U^X_{ft} (4)
Productivity:	Panel A: Log real VA per worker				Panel B: Log TFPR Olley-Pakes			
Productivity	0.0117***	0.0003	0.0114***	0.0117***	0.0069**	0.0001	0.0067**	0.0069**
	[0.0024]	[0.0012]	[0.0027]	[0.0024]	[0.0029]	[0.0015]	[0.0032]	[0.0029]
U^X_{ft}				-0.9474***				-0.9557***
				[0.0093]				[0.0099]
Capital Intensity	-0.0114***	0.0023*	-0.0138***	-0.0115***	-0.0088***	0.0014	-0.0102***	-0.0089***
	[0.0025]	[0.0013]	[0.0029]	[0.0025]	[0.0027]	[0.0014]	[0.0031]	[0.0027]
Skill Intensity	0.0063**	-0.0005	0.0068*	0.0063**	0.0092***	-0.0015	0.0107***	0.0093***
	[0.0032]	[0.0016]	[0.0036]	[0.0032]	[0.0034]	[0.0017]	[0.0038]	[0.0034]
N	145,534	145,534	145,534	145,534	134,817	134,817	134,817	134,817
R^2	0.7916	0.9604	0.8264	0.8550	0.7986	0.9629	0.8314	0.8586
Productivity:	Panel C: Log TFPR Levinsohn-Petrin				Panel D: Log TFPR Ackerberg-Caves-Frazer			
Productivity	0.0135***	-0.0003	0.0138***	0.0135***	0.0090***	-0.0001	0.0091***	0.0090***
	[0.0026]	[0.0013]	[0.0029]	[0.0026]	[0.0025]	[0.0013]	[0.0028]	[0.0025]
U^X_{ft}				-0.9571***				-0.9585***
				[0.0100]				[0.0099]
Capital Intensity	-0.0066**	0.0012	-0.0078**	-0.0067**	-0.0088***	0.0013	-0.0101***	-0.0088***
	[0.0027]	[0.0014]	[0.0031]	[0.0027]	[0.0027]	[0.0014]	[0.0030]	[0.0027]
Skill Intensity	0.0065*	-0.0013	0.0078**	0.0066*	0.0068**	-0.0008	0.0076**	0.0069**
	[0.0034]	[0.0017]	[0.0038]	[0.0034]	[0.0034]	[0.0017]	[0.0038]	[0.0034]
N	134,434	134,434	134,434	134,434	135,334	135,334	135,334	135,334
R^2	0.7978	0.9632	0.8312	0.8584	0.7977	0.9632	0.8315	0.8589
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comprises the matched CCTS-ASIF 2000–2006 panel of non-intermediary firms, in all years in which the firm both imports and exports. Each panel reports a separate set of regressions using the firm productivity measure indicated in the panel heading; for each productivity measure, observations with productivity smaller than the 1st percentile or larger than the 99th percentile are dropped. Standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. All columns include firm and industry-by-year fixed effects.

In Panel C of Table 6, we consider firm age as a broad measure of experience. We infer this from the year of a firm's establishment as reported in the ASIF; to accommodate entrants during our sample period, we work with log(age + 1). In Panel D, we focus on experience specifically with production for and sales to foreign markets. For a firm that is active in year t, we capture this by the log of its cumulative past exports up to year $t-1$ as recorded in the CCTS. As there is potential censoring of this variable for firms that began exporting prior to 2000, we include an interaction term between log cumulative past exports as described and an indicator variable for whether the firm was an active exporter in 2000.[32] The regression results indicate that as companies mature and become more experienced participants in global trade, they tend to expand the number of production stages they conduct by importing more upstream inputs, while shifting slightly the positioning of their exports closer to final demand (Columns 1–3); this finding does not depend on whether or not we control for the positioning of a firm's exports (Column 4).

The effects of firm size and experience that can be inferred from Table 6 are fairly sizeable, when benchmarked using the mean annual within-firm change for each firm attribute (as in the earlier calculations with the productivity measures). To give two examples, the mean annual within-firm shift in log sales among Chinese firms can explain an increase of 0.006 in the span of stages performed, while the corresponding effect of export experience (log cumulative past exports) is an even larger expansion of 0.025 in $U^M_{ft} - U^X_{ft}$.[33]

We have performed several checks to verify the robustness of these relationships of firms' production staging to firms' productivity, size and experience. First, as mentioned earlier, all findings hold when omitting the controls for firms' capital and skill intensity. The baseline specifications with these controls should be interpreted with a grain of salt to the extent that productivity, size and experience are primitives that determine firm operations including skill and capital use. The estimates in Tables 5-6 nevertheless suggest that expansion into more production stages is associated with lower capital intensity and higher skill intensity. Separately, we have confirmed that the results are not driven by differences across firms in their participation in processing versus

[32] The results are very similar if we instead use firms' cumulative past imports – constructed and allowing for censoring in the regression in an analogous manner – to capture experience with foreign suppliers.

[33] The mean annual within-firm change in log sales in our sample is 0.167; based on the Panel A, Column 3 coefficient estimate, this translates into an increase in the span of stages of $0.0335 \times 0.167 \approx 0.006$. For cumulative exports, we focus on the coefficient of the main effect term, as the interaction with the dummy for whether cumulative exports might be censored is not statistically significant. The mean annual within-firm change in log past exports is 1.082, implying a shift in the span of stages of $0.0235 \times 1.082 \approx 0.025$.

Table 6
Firm size, experience and global production line position.

Dep variable:	U^M_{ft} (1)	U^X_{ft} (2)	U^M_{ft} - U^X_{ft} (3)	U^M_{ft} - U^X_{ft} (4)	U^M_{ft} (1)	U^X_{ft} (2)	U^M_{ft} - U^X_{ft} (3)	U^M_{ft} - U^X_{ft} (4)
Size:	Panel A: Log Sales				Panel B: Log Employment			
Size	0.0293***	-0.0042**	0.0335***	0.0295***	0.0260***	-0.0038	0.0298***	0.0262***
	[0.0033]	[0.0017]	[0.0036]	[0.0033]	[0.0044]	[0.0024]	[0.0049]	[0.0044]
U^X_{ft}				-0.9524***				-0.9536***
				[0.0090]				[0.0090]
Capital Intensity	-0.0094***	0.0016	-0.0109***	-0.0094***	-0.0039	0.0015	-0.0054*	-0.0040
	[0.0024]	[0.0012]	[0.0027]	[0.0024]	[0.0026]	[0.0014]	[0.0029]	[0.0026]
Skill Intensity	0.0069**	0.0001	0.0068**	0.0069**	0.0132***	-0.0001	0.0133***	0.0132***
	[0.0030]	[0.0015]	[0.0033]	[0.0030]	[0.0031]	[0.0016]	[0.0034]	[0.0031]
N	152,917	152,917	152,917	152,917	153,426	153,426	153,426	153,426
R^2	0.7889	0.9596	0.8242	0.8534	0.7888	0.9596	0.8235	0.8529
Experience:	Panel C: Log (Age+1)				Panel D: Log Cumulative Past Exports			
Experience	0.1802***	-0.0082	0.1884***	0.1806***	0.0207***	-0.0028**	0.0235***	0.0209***
	[0.0126]	[0.0061]	[0.0140]	[0.0126]	[0.0030]	[0.0014]	[0.0033]	[0.0030]
Experience× Censored					-0.0044	-0.0046*	0.0003	-0.0041
					[0.0047]	[0.0024]	[0.0051]	[0.0046]
U^X_{ft}				-0.9531***				-0.9425***
				[0.0088]				[0.0114]
Capital Intensity	-0.0125***	0.0018	-0.0142***	-0.0125***	-0.0097***	0.0026*	-0.0123***	-0.0099***
	[0.0024]	[0.0012]	[0.0027]	[0.0024]	[0.0029]	[0.0014]	[0.0032]	[0.0029]
Skill Intensity	0.0062**	0.0001	0.0061*	0.0062**	0.0037	0.0008	0.0028	0.0036
	[0.0029]	[0.0015]	[0.0033]	[0.0029]	[0.0036]	[0.0017]	[0.0039]	[0.0036]
N	156,358	156,358	156,358	156,358	109,803	109,803	109,803	109,803
R^2	0.7897	0.9592	0.8235	0.8532	0.8089	0.9692	0.8443	0.8667
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comprises the matched CCTS-ASIF 2000–2006 panel of non-intermediary firms, in all years in which the firm both imports and exports. Each panel reports a separate set of regressions using the firm size or experience measure indicated in the panel heading; for each panel, observations where the size/experience measure is smaller than the 1st percentile or larger than the 99th percentile are dropped. In Panel D, the "Censored" indicator variable is equal to 1 if the firm reports positive exports in 2000, so that its cumulative exports are potentially left-censored due to the lack of firm-level export data pre-2000. Standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. All columns include firm and industry-by-year fixed effects.

ordinary trade, as all the findings in Tables 5-6 are robust to controlling for the share of a firm's exports conducted under the processing trade regime.[34] Third, our results continue to hold for different constructions of the firm-level upstreamness measures, such as when we retain only products that map to manufacturing industries, or when we drop minerals (HS codes 25–27).

We have further explored whether the relationship between productivity and the upstreamness of a firm's trade flows might exhibit heterogeneity across firm ownership types. Appendix Table 5 presents results from estimating (7) with firm productivity Z_{ft} interacted with a set of dummies for the firm's ownership status (respectively, SOE, PVT, or JVC/MNC).[35] Interestingly, the positive correlation between firm productivity and the span of stages is strongest for joint ventures and multinational affiliates across all revenue-based productivity measures; while the effect is generally positive for private domestic firms, these coefficients tend to be less precisely estimated. A potential explanation could be that firms with significant foreign ownership shares are less financially constrained than firms under different ownership structures (c.f., Manova et al., 2015), and can therefore more readily expand their span of stages in response to productivity improvements.[36]

[34] Alternatively, the export processing share can itself be interpreted as a proxy for a firm's experience with international trade, as the processing trade regime is often viewed as a platform through which Chinese firms started engaging in GVCs. Appendix Table 4, Panel B, reports regressions where we adopt this perspective and use the export processing share as the firm attribute Z_{ft} in specification (7). We find that firms that conduct a greater share of processing trade import products (presumably inputs) that are more upstream, export products closer to final demand, and thus span a greater set of production stages in China. This could be because producing on behalf of a foreign buyer engenders knowledge transfer that enables Chinese firms to undertake more manufacturing steps.

[35] Note that these three ownership types fully span all firms in our sample, so that the main effects of the ownership dummies are subsumed by the firm fixed effects.

[36] We have further examined whether the patterns we have documented might also be present in cross-sectional variation. To do so, we replace the firm fixed effects in (7) with a full set of GB/T 4-digit industry by city by ownership-type dummies, while retaining the industry-by-year fixed effects, φ_{st}. Appendix Table 6 reports the results from this exercise. We do not obtain as consistent a pattern of correlations across all four TFP measures, possibly because these regressions do not control as thoroughly for potential firm-level variables that could be affecting both firm productivity and its production staging decisions. For log real value added per worker and TFP ACF (Panels A and D), higher firm productivity is positively correlated with both the upstreamness of imports and exports; we do find that higher productivity is associated with a wider span of stages, but only if we condition on U^X_{ft} (Column 4), suggesting that the proximity of the firm's exports to final demand is a key omitted variable. On the other hand, the effect of productivity on $U^M_{ft} - U^X_{ft}$ is not precisely estimated for TFPR OP and TFPR LP (Panels B and C).

4.2.2. IV causality

The results from OLS specification (7) reveal informative systematic correlations between key attributes of Chinese firms and their production line position. We now provide complementary evidence based on two-stage-least-squares estimation, which indicates that changes in productivity can have causal effects on firms' production staging.

Our IV strategy seeks to exploit plausibly exogenous positive shocks to foreign demand, which can in turn raise firms' exports and thereby total sales. Such shocks can further boost firm TFP if they trigger changes in firms' production processes that generate increasing returns. In the context of China's exporters, it has been argued that positive shocks to export demand can facilitate learning-by-exporting about consumer preferences in foreign markets and about know-how at the technological and quality frontiers (e.g., Park et al., 2010). Along similar lines, increases in export revenue can make feasible investments to upgrade a firm's production technology or reorganize its internal processes (e.g., Brandt et al., 2014). A positive shock to foreign demand can thus raise revenue-based measures of firm productivity, such as those we have computed for the ASIF-CCTS panel.

We construct our $ExportIV_{ft}$ instrument by first computing a shift-share projected growth rate in foreign demand for firm f's products from year $t-1$ to t, to capture movements at the firm-year level. This is done by taking a weighted-average of the year-on-year growth in rest-of-the-world export flows; in particular, we draw on the CEPII BACI dataset for its information on total exports emanating from the rest of the world (i.e., excluding China), $X_{ROW,cpt}$, disaggregated by destination country c and HS 6-digit product p. To capture the degree of exposure of each firm f on the exporting front to these country-by-product trade shocks, we use as weights the share of country c and product p in firm f's export profile, $\frac{X_{fcp,0}}{X_{f,0}}$, in the first year (indexed by 0) where we observe firm f exporting in the CCTS data. Combining this projected growth rate with information on the one-year lagged level of f's exports, we obtain a predicted (log) level of firm f's exports in year t, which will serve as our IV. The precise formula for the foreign demand instrument is given by:

$$ExportIV_{ft} = \ln\left(X_{f,t-1}\left(1+\sum_{c\neq China,p}\frac{X_{fcp,0}}{X_{f,0}}\frac{X_{ROW,cpt}-X_{ROW,cp,t-1}}{X_{ROW,cp,t-1}}\right)\right), \tag{9}$$

where we exclude China as a destination country c in the weighted average in (9).[37] Note that for each firm f, we construct $ExportIV_{ft}$ for years in which $t-1>0$, so that the predicted country-by-product export growth rates in (9) do not use data from years that overlap with the initial year 0 for which export share weights are available for the firm in question. Given that our ASIF-CCTS panel starts in 2000, this means that we have been conservative in constructing $ExportIV_{ft}$ only for 2002–2006. The above constitutes a valid instrument if the shifts in foreign demand captured by the rest-of-the-world trade shocks are exogenous from the perspective of individual Chinese firms f, and insofar as the consequent effects on firms' production staging decisions are mediated through their effect on firm productivity.

Table 7 presents our estimates from re-running (7) with $ExportIV_{ft}$ as an instrumental variable for each of the measures of firm productivity. These reproduce the pattern of correlations seen earlier in Table 5, and indicate that there is a causal dimension in the effects of shocks to firm productivity on Chinese firms' GVC positioning. The first stage in Column 1 confirms that $ExportIV_{ft}$ has strong predictive power: the IV has an expected positive and significant effect on firm productivity, and the F-statistics are moreover large with the exception of log TFPR OP (Panel B). The results for the second stage in Columns 2–5 corroborate the earlier OLS analysis. The point estimates we obtain are moreover considerably larger in all panels, yielding statistically significant results (except for log TFPR OP). This is consistent both with measurement error in firm productivity and with larger responses to exogenous shocks to productivity compared to changes that are endogenously initiated by the firm. Consequently, the implied magnitudes of these effects on the span of stages is much bigger: For example, for the mean within-firm annual change in log TFPR LP quoted in Section 4.2.1, the implied increase in $U^M_{ft} - U^X_{ft}$ is now 0.039, larger than the actual within-firm annual change of 0.029 seen in the data.[38]

In Appendix Table 7, we present results for the impact of firm size when using the predicted foreign demand variable as an IV for log sales or log employment. These confirm that a rise in foreign demand has a direct positive effect on the scale of firm production that should in principle precede observed changes in productivity. In line with this logic, we do find in the respective first-stage regressions that the estimated effects of $ExportIV_{ft}$ on log sales and log employment are larger, when compared against the corresponding effects on any of the four TFP measures in Table 7.

Much like exogenous shocks to foreign demand, exogenous shocks to foreign supply can also move firm productivity and size. A rise in foreign productivity or product quality may induce Chinese firms to source more foreign inputs, lower their marginal production costs, and thereby increase their TFP. This can occur directly through improved access to superior or cheaper equipment, or indirectly through complementarities between production inputs and production technologies or management practices (e.g., Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Goldberg et al., 2010; Halpern et al., 2015). Appendix Table 8 presents IV regressions where we use an $ImportIV_{ft}$ instrument that is the analogue of (9) for Chinese firms' imports, based on how shocks experienced in rest-of-the-world imports (disaggregated by origin country and HS6 product) potentially impact

[37] The country-by-HS6-product export growth rates exhibit both large positive and negative extreme values, and so we winsorize $(X_{ROW,cpt} - X_{ROW,cp,t-1})/X_{ROW,cp,t-1}$ at its 10th and 90th percentiles when calculating $ExportIV_{ft}$.

[38] Specifically, using the Column 4 point estimate in Panel C of Table 7, and following steps similar to footnote 29 in Section 4.2.1, we have: $0.1966 \times 0.198 \approx 0.039$.

Table 7
Firm productivity, IV evidence.

Dep variable:	1st Stage (1)	U^M_{ft} (2)	U^X_{ft} (3)	U^M_{ft} - U^X_{ft} (4)	U^M_{ft} - U^X_{ft} (5)	1st Stage (1)	U^M_{ft} (2)	U^X_{ft} (3)	U^M_{ft} - U^X_{ft} (4)	U^M_{ft} - U^X_{ft} (5)
Productivity:	Panel A: Log real VA per worker					Panel B: Log TFPR Olley-Pakes				
Export IV	0.0127***					0.0050*				
	[0.0034]					[0.0029]				
Productivity		0.6406**	-0.0769	0.7174**	0.6449**		1.7099	-0.1403	1.8502	1.7145
		[0.2635]	[0.1336]	[0.3036]	[0.2639]		[1.1400]	[0.3477]	[1.2669]	[1.1401]
U^X_{ft}					-0.9441***					-0.9672***
					[0.0176]					[0.0344]
N	80,693	80,693	80,693	80,693	80,693	77,681	77,681	77,681	77,681	77,681
R^2	0.8679	0.7055	0.9737	0.7554	0.7947	0.7336	0.1324	0.9721	0.2925	0.3922
F-stat		14.19	14.19	14.19	14.21		2.908	2.908	2.908	2.923
Productivity:	Panel C: Log TFPR Levinsohn-Petrin					Panel D: Log TFPR Ackerberg-Caves-Frazer				
Export IV	0.0481***					0.0141***				
	[0.0036]					[0.0035]				
Productivity		0.1743***	-0.0223	0.1966***	0.1756***		0.6564***	-0.0782	0.7345**	0.6605***
		[0.0574]	[0.0351]	[0.0672]	[0.0574]		[0.2487]	[0.1192]	[0.2864]	[0.2492]
U^X_{ft}					-0.9431***					-0.9478***
					[0.0150]					[0.0184]
N	77,144	77,144	77,144	77,144	77,144	78,018	78,018	78,018	78,018	78,018
R^2	0.9013	0.8231	0.9762	0.8578	0.8769	0.8783	0.6977	0.9748	0.7498	0.7899
F-stat		175.0	175.0	175.0	175.0		16.34	16.34	16.34	16.36
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
K and H intensity	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comprises the matched CCTS-ASIF 2000–2006 panel of non-intermediary firms, in all years in which the firm both imports and exports. Each panel reports a separate set of regressions using the firm productivity measure indicated in the panel heading; for each productivity measure, observations with productivity smaller than the 1st percentile or larger than the 99th percentile are dropped. The IV is a firm-level predicted log export variable for year *t*, constructed from: (i) observed rest-of-the-world export shocks (less exports from China) broken down by destination country and product between year *t-1* and *t*; (ii) each firm's country-product export shares in the first year in which they record exports; and (iii) lag firm-level exports in year *t-1*. Standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. All columns include firm and industry-by-year fixed effects.

the firm *f* given its initial import profile. The results this yields are very much consistent with what we have seen in Table 7 from using $ExportIV_{ft}$.[39]

4.3. Firm value added, costs, assets, and profits

We next establish that changes in firms' global production line position are accompanied by shifts in their value added, input usage, cost and asset structure, as well as profits. Here, we work off specification (8) using different indicators for firm operations, Y_{ft}, as the left-hand side variable.

Firm Fact 2: *When firms span more production stages (in China), they increase value added in production, total input purchases, and total wagebill proportionately with sales.*

In the first two columns of Table 8, we examine the relationship between firms' span of stages and the amount of value they add in production. Column 1 demonstrates that value added rises sharply as the distance between the position of firms' imports and exports in GVCs widens, with a one-stage increase in $U^M_{ft} - U^X_{ft}$ associated with real value added that is on average 3.1% higher. This relationship may appear at first glance to be mechanical: When a firm spans more stages, one might naturally expect it to be responsible for a greater amount of value added in the production process. Column 2 shows that this partial correlation is instead explained by an associated scaling up of firm operations. We condition here on log real firm sales to capture the firm's gross output. Value added indeed moves in step with total sales, with a point estimate close to 1. Moreover, this proportional

[39] More specifically, $ImportIV_{ft}$ is computed as:

$$ImportIV_{ft} = \ln\left(M_{f,t-1}\left(1 + \sum_{c \neq China,\, p} \frac{M_{fcp,0}}{M_{f,0}} \frac{M_{ROW,cpt} - M_{ROW,cp,t-1}}{M_{ROW,cp,t-1}}\right)\right),$$

where $M_{ROW,cpt}$ is the value of total imports of HS6-digit product *p* by the rest of the world (excluding China) from country *c* in year *t*; $\frac{M_{fcp,0}}{M_{f,0}}$ is the share of country *c* and product *p* in firm *f*'s imports, in the initial year 0 the firm records imports in the CCTS; and $M_{f,t-1}$ is firm *f*'s total imports in year $t-1$. $(M_{ROW,cpt} - M_{ROW,cp,t-1})/M_{ROW,cp,t-1}$ is winsorized at its 10th and 90th percentiles. Although it is possible to use both $ExportIV_{ft}$ and $ImportIV_{ft}$ simultaneously as instruments, we do not report these results as they tend not to pass the over-identification test.

Table 8
Firm global production line position, inputs and value added.

Dep variable:	Log Real Value Added		Log Real Total Inputs		Log Wagebill		Imports / Total Inputs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
U^M_{ft} - U^X_{ft}	0.0309***	0.0009	0.0288***	-0.0013	0.0307***	0.0049	-7.1574***	-6.3846***
	[0.0045]	[0.0030]	[0.0036]	[0.0016]	[0.0051]	[0.0043]	[0.3179]	[0.3109]
Log Real Sales		0.9619***		0.9229***		0.7141***		-21.4526***
		[0.0040]		[0.0030]		[0.0072]		[0.6373]
N	145,216	144,131	150,286	149,266	153,286	148,591	153,006	147,326
R^2	0.8769	0.9357	0.9104	0.9760	0.9393	0.9541	0.7436	0.7589
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
K & H Intensity	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comprises the matched CCTS-ASIF 2000–2006 panel of non-intermediary firms, in all years in which the firm both imports and exports. Each pair of columns reports a separate set of regressions using a different measure of firm inputs and value added, as indicated in the column heading; for each firm input/value added measure, observations smaller than the 1st percentile or larger than the 99th percentile are dropped. Standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. All columns include firm and industry-by-year fixed effects. The firm-level measures of capital and skill intensity.

adjustment fully explains the unconditional correlation between value added and $U^M_{ft} - U^X_{ft}$, as the coefficient on the latter is now statistically indistinguishable from 0.[40]

We next consider the pattern of firms' variable input use. We find that firms significantly increase their total input purchases when they broaden the scope of manufacturing steps they undertake in China. Overall, a widening in $U^M_{ft} - U^X_{ft}$ by one production stage is associated within firms with real input purchases that are 2.9% higher (Column 3). We obtain the same pattern when looking at labor inputs, as captured by firms' total wagebill (computed from the ASIF as the average wage times total employment). There, a unit increase in a firm's span of stages corresponds to a total outlay on wages that is 3.1% greater (Column 5). As with value added, these increases in variable costs entirely reflect an expansion in the scale of firms' output, as the partial correlations are not statistically significant once we condition on log real sales (Columns 4 and 6).

Interestingly, we find in Column 7 that the span of a firm's operations in global production lines, $U^M_{ft} - U^X_{ft}$, is negatively correlated with the ratio of its imports relative to its total intermediate input purchases. This pattern persists when controlling for the firm's log sales (Column 8), indicating that it is not merely an artefact of an expansion in the overall scale of firm operations. Put otherwise, as the scope of stages undertaken in China has widened, there appears to have been some switching within firms towards procuring a greater share of inputs from domestic sources, though we caution that we cannot say anything more definitive since we do not directly observe the domestic production network or the composition of firms' domestic inputs. In Appendix Table 9 (Columns 1–2), we report an analogous pattern on the exporting side: the span of stages conducted within China correlates positively with a firm's export intensity, as proxied by its export-to-sales ratio. Taken together, these hint at some subtle shifts in the manner of Chinese firms' engagement in GVCs that warrant closer study in future work.

Firm Fact 3: *When firms span more production stages (in China), they increase their fixed costs and assets. They also earn higher profits that rise proportionately with sales.*

In Table 9, we consider respectively the log level of net fixed plant, property and equipment (Columns 1–2) and its share in total book-value assets (Columns 3–4). These measures reflect respectively how important the stock of long-term capital is to firm operations in an absolute and in a relative sense. In the remainder of the table, we instead study the log value of inventories (Columns 5–6) and their value relative to total assets (Columns 7–8). Outstanding inventories constitute a flow of short-term fixed costs of manufacturing and maintaining supply capacity.

We observe that when firms manage more production stages (in China), they maintain more fixed assets and incur higher fixed costs: The value of fixed assets and inventories, as well as each of their shares in total firm assets, all rise with the span of production stages. As an illustration of the implied magnitudes, based on the point estimates in Columns 1 and 5, a one-stage widening in $U^M_{ft} - U^X_{ft}$ is associated respectively with 1.5% higher investment in fixed assets and 2.4% more inventory holdings.[41] Together, the patterns in Tables 8-9 are consistent with firms incurring higher fixed and variable costs when they undertake more manufacturing stages within China.

We explore last how a firm's global production line position relates to its performance in terms of profits. We estimate specification (8) using a measure, Π_{ft}, of firm-level profits, computed as total real profits from operations after applying industry-specific output deflators. The summary statistics in Table 1 indicate that this profit variable exhibits a particularly large dispersion;

[40] These findings in Column 2 are unchanged even if we were to further control for U^X_{ft} to capture the proximity to final demand of the products the firm exports. This statement on robustness applies to each of the subsequent firm attributes considered as left-hand side variables in Tables 8-9 and Appendix Table 9 (available on request).

[41] As log inventories remain significantly correlated with $U^M_{ft} - U^X_{ft}$ even after controlling for log sales (Column 6, Table 9), one might at first glance draw the conclusion that this measure of fixed costs rises more than sales as the firm engages in a wider span of stages. Note though that the estimated coefficient of log real sales (0.3838) in this regression is much below 1. When we re-run this regression with the log inventories-to-sales ratio as the dependent variable (i.e., moving log real sales to the left-hand side), we obtain a coefficient on $U^M_{ft} - U^X_{ft}$ of −0.0079 with a standard error of 0.0052 (not significant at the 10% level), consistent with fixed costs rising proportionately with sales.

Table 9
Firm global production line position, assets and cost structure, and profits.

Dep variable:	Log Fixed Assets		Fixed Assets/Total Assets		Log Inventories		Inventories/Total Assets		Profits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
U^M_{ft} - U^X_{ft}	0.0145***	0.0025	0.0036***	0.0037***	0.0244***	0.0111**	0.0033***	0.0033***	101.88***	21.42
	[0.0026]	[0.0022]	[0.0006]	[0.0006]	[0.0049]	[0.0048]	[0.0006]	[0.0006]	[29.88]	[28.08]
Log Real Sales		0.3573***		-0.0076***		0.3838***		-0.0009		2,882.86***
		[0.0037]		[0.0009]		[0.0072]		[0.0009]		[39.37]
N	153,323	148,516	153,951	148,110	148,932	144,640	154,483	148,581	133,167	131,802
R^2	0.9721	0.9790	0.8549	0.8570	0.8742	0.8811	0.7154	0.7183	0.7262	0.7553
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
K & H Intensity	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comprises the matched CCTS-ASIF 2000–2006 panel of non-intermediary firms, in all years in which the firm both imports and exports. Each pair of columns reports a separate set of regressions using a different measure of firm assets, inventories, or profits, as indicated in the panel heading. For each firm asset/inventory measure, observations smaller than the 1st percentile or larger than the 99th percentile are dropped. For the real profit measure, given its greater skew, observations smaller than the 5th percentile and larger than the 95th percentile are dropped. Standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. All columns include firm and industry-by-year fixed effects. The firm-level measures of capital and skill intensity.

bear in mind that real profits for any given firm-year can be negative, and the raw data contain both large positive and negative reported profits. We therefore trim the top and bottom 5% of observations from our sample. The regressions confirm that firms earn systematically higher profits when they complete more production stages in GVCs (Column 9). At the same time, these profits appear to rise as a consequence of the scaling up of firms' overall operations, as the partial correlation vanishes once we control for log firm sales (Column 10). Consistent with this last result, we report in Appendix Table 9 that $U^M_{ft} - U^X_{ft}$ does not correlate significantly with various measures of firm profitability, including the profit-to-sales ratio, the profit-to-value-added ratio, and return on assets (defined as profits relative to total assets).[42]

5. Towards a conceptual framework

The empirical analysis has uncovered new stylized facts about the joint evolution of Chinese firms' attributes and their production line position over the firm lifecycle. We propose here a conceptual framework that can rationalize these facts and give them an internally consistent economic interpretation. We consider a stylized, partial-equilibrium setting, in which the firm takes certain market conditions as given, such as the price of intermediate goods at different stages of completion. Our purpose is to highlight in as basic a framework as possible some key trade-offs for understanding a firm's span of production stages, that more complete models – incorporating considerations related for example to market power – can build on in future work.

5.1. Set-up

The production of final goods in any given industry requires the completion of a continuum of stages. These stages are uniquely sequenced due to technological reasons; for example, the tyres of a car need to be ready before the rolling chassis can be assembled. We index the production stages by $u \in [1, \infty)$, where a higher u refers to a stage that is more upstream and positioned earlier in the production sequence. In particular, the most upstream stage at the start of the production line is indexed by $u = \infty$, while the completed final good is indexed by $u = 1$. We adopt this convention to be consistent with the empirical measure of upstreamness in the prior sections.

We consider the decision problem of a firm that is active in one particular industry, over the measure of production stages to perform. The output of a firm that has chosen its span of production stages to be between $u = U^M$ and $u = U^X$ is given by:

$$q = \theta\left(\int_{U^X}^{U^M} x(u)^{\alpha} du + q_M^{\alpha}\right)^{\frac{\rho}{\alpha}}, \tag{10}$$

where $1 \leq U^X < U^M$ and $\alpha, \rho \in (0,1)$. Here, q_M is the quantity of the semi-finished good that has been completed up to stage U^M, which the firm purchases as an intermediate input; to be clear, all stage inputs for $u \in [U^M, \infty)$ have already been built into this intermediate input when it is purchased. The production stages from $u = U^M$ to $u = U^X$ are then performed, with the firm choosing the quantity $x(u)$ of inputs for each of these stages.[43] The output q that the firm generates is in turn a semi-finished good that has been completed up to stage U^X.

[42] For these latter variables, we first drop the tail 5% of observations for total real profits; we then compute the respective ratios and further drop the tail 1% of observations for each profit margin measure thereafter.
[43] We have emphasized the sequentiality of the production stages to be in keeping with prior modeling work on production chains such as Harms et al. (2012), Costinot et al. (2013), and Antràs and Chor (2013). One can, however, interpret the production function in (10) as one in which all stages $u \in [U^X, U^M]$ are performed simultaneously by the firm, such that the insights we derive do not depend crucially on the timing of these production stages.

While the model is agnostic about where intermediate input q_M is purchased from or where output q is sold, it is natural in the context of China for us to associate U^M and U^X with the firm-level import and export upstreamness measures constructed earlier. As in the earlier empirical work, we do not specify whether the firm performs stages $u \in [U^X, U^M]$ in-house or fulfills them via arm's length purchases from domestic suppliers. As currently formulated, the implicit assumption is that the costs associated with in-house production of a given stage u are not too dissimilar from that which would be incurred when outsourcing to a domestic supplier. A richer model that takes this domestic sourcing decision more explicitly into account would be a meaningful direction for future work, especially if its predictions could be explored with more detailed data.

In (10), the intermediate input q_M and the stage inputs $x(u)$ are combined in a CES manner, with elasticity of substitution equal to $1/(1-\alpha) > 1$.[44] The parameter $\rho \in (0,1)$ captures the degree to which the output of the firm is subject to decreasing returns to scale. Given the price-taking assumptions that we adopt below, ρ needs to be strictly smaller than 1 in order for the size of the firm to be uniquely pinned down.

The productivity of the firm is given by θ. To fix ideas, one can think of θ as coming from a productivity draw that the firm receives upon its successful entry into the industry (Melitz, 2003), which reflects the efficiency of its assembly technologies and/or the effectiveness of its management practices. For our purposes, we will treat θ as a firm-specific attribute and consider comparative statics with respect to it, to explore how the span of stages the firm performs would respond to exogenous shocks to its productivity. A richer dynamic framework would model the evolution of this productivity over the firm lifecycle, and how this might affect firm entry and exit decisions; these are pertinent issues that we abstract from here. Note that θ can be interpreted alternatively as a quality term, with changes in θ reflecting shocks to market demand for the firm's output.

We assume for simplicity that the firm is small within the industry and that it takes prices as given. There is moreover an open competitive market for semi-finished goods at all stages of completion $u \in [1, \infty)$ with price schedule $p(u)$. We posit that $p'(u) < 0$: the market price of a more upstream good is lower, as these embody fewer completed production stages. As an example, this means that there is a market price for the raw rubber needed to manufacture four tyres, and that this is lower than the purchase price for a set of completed tyres.[45]

The firm incurs two costs for each production stage $u \in [U^X, U^M]$ that it performs: (i) a variable cost, $c(u)$, per unit of the stage input $x(u)$; and (ii) a per period fixed cost, $f(u)$, which applies as long as $x(u) > 0$. One can view $c(u)$ as the cost of labor inputs that are required to produce each unit of the stage input $x(u)$. In turn, the $f(u)$ can be interpreted as an overhead usage cost of assets and equipment necessary for the execution of the production stage u. For convenience, we will assume that both $c(u)$ and $f(u)$ are differentiable functions.[46]

The firm's profit function is thus given by:

$$\pi = p\left(U^X\right)q - p\left(U^M\right)q_M - \int_{U^X}^{U^M} c(u)x(u)du - \int_{U^X}^{U^M} f(u)du, \tag{11}$$

this being the revenue from sales of the stage-U^X good, less the cost of q_M units of the stage-U^M intermediate input, as well as the variable and fixed costs for the stages $u \in [U^X, U^M]$. Given knowledge of its productivity θ, the firm then chooses: (i) the cut-off stages, U^M and U^X; (ii) the quantity q_M of the upstream intermediate input to purchase; and (iii) the quantity of $\{x(u)\}_{u=U^X}^{u=U^M}$ for each stage input. These decisions are made to maximize the firm's profits as specified in (11). We will focus for simplicity on a situation where the firm's profit maximization problem yields an interior solution that yields positive profits.

5.2. Firm behavior

We explore how an increase in a firm's productivity can impact the optimal span of stages that it engages in. A shock to θ would lead a profit-maximizing firm to re-evaluate the positions of its cut-off stages U^X and U^M, while accordingly adjusting the quantity q_M of the upstream intermediate to procure and the quantities $x(u)$ of stage inputs. We focus on the conditions under which these firm-level responses would be consistent with the empirical patterns documented in Sections 3 and 4 for the global production line position of Chinese firms.

Holding all else constant, a positive shock to productivity θ would raise the firm's output and hence its revenues. In principle, this would make it feasible for the firm to conduct a larger range of production stages, by purchasing a more upstream intermediate input (i.e., increasing U^M), and/or by assembling a product that is closer to the final good (i.e., decreasing U^X). Intuitively, an increase in U^M would lower the price $p(U^M)$ of the more upstream intermediate input that must be purchased (since $p'(u) < 0$), but this needs to be compared against the fixed and variable costs incurred when the firm takes on responsibility for the inframarginal stages. Similarly, a decrease in U^X means that the firm would be able to fetch a higher price $p(U^X)$ for selling a more finished good, but this needs to be weighed against the additional fixed and variable costs of completing more stages.

The framework in Section 5.1 sheds light on these key trade-offs. The model set-up is fairly general and can accommodate different shifts in a firm's production span in response to shocks to its productivity. As should be clear though, what is important is

[44] This CES formulation of the production function over stage inputs is similar to that in Antràs and Chor (2013) and Alfaro et al. (2019).

[45] In practice, some inputs might need to be customized to the specific needs of the firm. Antràs and Chor (2013) and Alfaro et al. (2019) study the implications of such specificity for production chains under incomplete contracts, where firm payoffs are pinned down by a bargaining process rather than market prices.

[46] The formulation of production costs here is flexible enough for $c(u)$ to differ across firms, which allows firms to exhibit comparative advantage in performing particular stages of production.

to understand the behavior of the firm's revenue and cost structure in the neighborhood of its initial cut-off stages U^M and U^X. As we establish in the Theory Appendix, the following condition is sufficient to guarantee that a rise in firm productivity lead to a widening of the span of production stages performed:

Sufficient Condition: (i) $\rho > \alpha$; and (ii) $\frac{f(U^M)}{p(U^M)q_M}$, $\frac{c(U^M)x(U^M)}{p(U^M)q_M}$, $\frac{f(U^X)}{p(U^X)q}$, $\frac{c(U^X)x(U^X)}{p(U^X)q}$ are sufficiently small.

We demonstrate in the Theory Appendix that the first-order conditions associated with the firm's profit maximization problem imply the following:

Proposition 1. Under the Sufficient Condition, a positive productivity shock will induce a firm to:

1. *expand its span of production stages ($\frac{d(U^M-U^X)}{d\theta}>0$) by purchasing a more upstream input ($\frac{dU^M}{d\theta}>0$) and selling output that is more proximate to final demand ($\frac{dU^X}{d\theta}<0$); and*
2. *use a higher quantity of the upstream input ($\frac{dq_M}{d\theta}>0$) and of all stage inputs ($\frac{dx(u)}{d\theta}>0\ \forall u \in [U^X, U^M]$).*

The Sufficient Condition lends itself to an intuitive interpretation. For Proposition 1 to hold, we require first that the firm's production function not be subject too strongly to decreasing returns to scale (condition (i)). This provides a baseline technological reason for a firm that has become more productive to raise its output, which it can achieve in part by expanding the span of stages it performs. Put otherwise, this implies complementarity between the scale of the firm and the scope of production stages it performs. In turn, condition (ii) describes a set of circumstances under which a more productive firm would find it optimal to purchase a more upstream intermediate input, while selling output that is more proximate to final demand. This will be the case so long as the firm has low fixed and variable costs in the neighborhood of its initial upstream cut-off stage U^M, relative to the costs incurred from purchasing the stage-U^M good as an intermediate input; this ensures that the firm would find it feasible to substitute towards performing more of these stages. Proposition 1 likewise requires that the fixed and variable costs associated with the U^X cut-off stage be sufficiently low, relative to the revenues received from selling a stage-U^X good, in order to make it profitable to take on more stages at this margin.

Relationship to Stylized Facts: It is useful to connect Proposition 1 with the empirical findings reported earlier. First, the predictions for how U^X, U^M and hence $U^M - U^X$ each respond to exogenous increases in firm productivity line up with *Firm Fact 1*. To the extent that more productive firms also exhibit a larger volume of total sales and are more likely to survive over time, the proposition can further rationalize the empirical patterns for firm size and experience and their strong correlation with the firm-level upstreamness measures.[47] In the proof in the Appendix, we further highlight that if we were to relax the requirement that fixed and variable costs, $\frac{f(U^X)}{p(U^X)q}$ and $\frac{c(U^X)x(U^X)}{p(U^X)q}$, in the neighborhood of the U^X cut-off stage be sufficiently small, this can mute (or even reverse) the predicted sign of $\frac{dU^X}{d\theta}$, even while retaining the prediction that $\frac{dU^M}{d\theta}>0$. This would be consistent with the pattern of results uncovered in Section 4.2.1, where the correlation between firm productivity and export upstreamness was relatively weak, whereas the positive correlation with import upstreamness (and hence the span of stages) was especially robust.

Second, Proposition 1 also provides a plausible explanation for the evolution of the overall import and export upstreamness of China's trade flows (*Macro Trends 1–3*). Evidence in the prior literature points to a secular trend in productivity growth among Chinese firms during our sample period (e.g., Brandt et al., 2012), which can generate the pattern of a rising U^M and a falling U^X in the aggregate.[48]

We derive several additional results from the firm's profit maximization problem. With an increase in firm productivity θ, profits π in (11) would rise even if U^X, U^M, q_M and the $x(u)$'s were held fixed at their original values. It follows that profits necessarily rise after taking into account any profit-maximizing adjustments that the firm might make to these key choice variables.

The solution to the firm's problem also pins down its inputs, costs, and value added. Under the Sufficient Condition, following an increase in θ, the firm's total fixed costs, $FC \equiv \int_{U^X}^{U^M} f(u)du$, would rise, given that U^M increases and U^X decreases. Since $\frac{dx(u)}{d\theta}>0$, the firm's total variable costs, $VC \equiv \int_{U^X}^{U^M} c(u)x(u)du$, would also increase. Turning next to the firm's value added, defined as total revenues less intermediate input purchases, $VA \equiv p(U^X)q - p(U^M)q_M$, notice that VA is equal to the sum of the firm's profits, total fixed costs, and total variable costs. Since these last three terms all increase with θ, value added also rises.

Lastly, the effect on the total outlay on intermediates, $p(U^M)q_M$, is more subtle: With a higher U^M, the market price of the intermediate input is lower since $p'(u) < 0$, but this also induces the firm to demand a higher quantity q_M of it. The Appendix shows that under the Sufficient Condition, the latter force dominates and the firm's total input expenditure grows.

We summarize these conclusions as:

Proposition 2. Under the Sufficient Condition, a firm that expands its span of production stages, $U^M - U^X$, after a positive productivity shock will also experience: 1. higher profits, π; 2. higher value added, VA; 3. higher total variable costs, VC; 4. higher total fixed costs, FC; and 5. higher intermediate input purchases, $p(U^M)q_M$.

[47] Appendix Table 1 confirms that in our Chinese firm-level data, log productivity and log sales are indeed positively correlated, with the correlation coefficient varying between 0.25 and 0.79, depending on the productivity measure.

[48] This steady increase in TFP over time is readily corroborated by the firm-level measures of productivity that we have constructed and used to establish our *Firm Facts*.

Relationship to Stylized Facts: Proposition 2 helps to rationalize *Firm Facts 2–3* as correlations among joint outcomes of the firm's profit maximization problem. This is in contrast to Proposition 1, which speaks directly to a causal relationship running from an increase in firm productivity to its production line position.

The first result in Proposition 2 – that profits rise when firms choose to span a wider segment of the production chain – is consistent with *Firm Fact 3*.[49] In turn, the shifts predicted in Proposition 2 are in line with the idea that expanding into more stages is associated with incurring more fixed costs (*Firm Fact 3*), expanding the use of variable inputs such as intermediates and labor (*Firm Fact 2*), and adding more value in production (*Firm Fact 2*). While we do not observe this directly in the data, *Firm Facts 2–3* together do suggest that when Chinese firms expand their span of stages, some of these additional production steps are performed in-house: If they were instead only substituting foreign suppliers with domestic suppliers, it would be harder to account for the rise in value added, fixed costs and variable costs within firms. Indeed, in the early years of China's trade liberalization, firms in industries that were particularly reliant on imported inputs arguably had few available substitutes among domestic suppliers to facilitate their manufacturing processes.

We return to an earlier finding from Section 4.3, where in conjunction with *Firm Fact 2*, we reported that firms that sport a wider span of stages in their global positioning also appear to import a smaller share of their inputs, while exporting a greater share of their output. The conceptual framework above does not speak directly to these patterns, as the model has been agnostic about the locations from which inputs are purchased and to which output is sold. It should be noted though that these last empirical patterns are not inherently at odds with the underlying structure of the model. For example, if part of the fixed costs that are incurred are related to identifying reliable domestic sources of customized inputs, this could explain why more productive firms that undertake more stages within China are also seeing a decrease in the share of inputs they import.

6. Conclusion

In this paper, we have examined how Chinese firms position themselves in global production lines, and documented how this position evolves over the firm lifecycle. First, for the country as a whole, there has been a sharp rise in the upstreamness of imports, a stable pattern in the upstreamness of exports, and a rapid expansion in production stages conducted in China over the 1992–2014 period. Second, using detailed firm-level data, we have found that firms span more stages as they grow more productive, bigger and more experienced. This expansion is accompanied by a rise in value added, input use, fixed assets and profits, even though profit margins are relatively unaffected. These patterns speak to how China's participation in GVCs has been shaping structural transformation at the level of its manufacturing firms. Finally, we have illustrated with a stylized model how these patterns can be explained in a production chain setting that features complementarities between the scope of stages a firm undertakes and the scale of its production.

Much scope remains for future work on this broad topic. With the rise in trade tensions between China and the US, as well as the global slowdown from the COVID-19 pandemic, it will be interesting to track how such developments that could uncouple cross-border supply chains might affect the GVC positioning of Chinese firms. Separately, it would be useful to pursue empirical studies beyond China, to document if similar trends are present for other fast-growing developing countries that have sought to engage in GVCs. Firm-level datasets that contain more detailed information on the product mix of domestic input purchases or on the identity of domestic suppliers would be particularly welcome, in order to shed light on the role that vertical integration might play in influencing a firm's span of stages. Such empirical findings would in turn inform the development of richer models of the interplay between firms' participation in GVCs and firm-level outcomes. Of particular interest in this regard are implications for the distribution of the gains from trade across firms and countries.

Data availability

Data and Program Files, Growing Like China: (Original data) (Sites.Google)

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2021.103445.

[49] Though we have also explored several measures of profitability such as the profit-to-sales ratio in the empirics, how this measure would shift with an increase in firm productivity is theoretically ambiguous since both profits and sales would rise. One would need additional assumptions in order to pin down the direction of change.

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